DEVELOPMENT OF AVAILABILITY AND SUSTAINABILITY SPARES OPTIMIZATION MODELS FOR AIRCRAFT REPARABLES

THESIS

Edmund K.W. Pek, Major (Military Expert 5), RSAF
(Republic of Singapore Air Force)

AFIT-ENS-13-S-4

DEPARTMENT OF THE AIR FORCE
AIR UNIVERSITY

AIR FORCE INSTITUTE OF TECHNOLOGY

Wright-Patterson Air Force Base, Ohio

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THESIS

Presented to the Faculty

Department of Operational Sciences

Graduate School of Engineering and Management

Air Force Institute of Technology

Air University

Air Education and Training Command

In Partial Fulfillment of the Requirements for the

Degree of Master of Science in Logistics and Supply Chain Management

Edmund K.W. Pek

Major (Military Expert 5), RSAF

September 2013

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Approved:

//signed//	05 September 2013
Dr. Alan W. Johnson (Chair)	Date
//signed//	05 September 2013
LtCol. Joseph R. Huscroft, Ph.D. (Member)	Date

AFIT-ENS-13-S-4

Abstract

The Republic of Singapore Air Force (RSAF) conducts Logistics Support Analysis (LSA) studies in various engineering and logistics efforts on the myriad of air defense weapon systems. In these studies, inventory spares provisioning, availability and sustainability analyses are key focus areas to ensure asset sustenance. In particular, OPUS10, a commercial-off-the-shelf software, is extensively used to conduct reparable spares optimization in acquisition programs. However, it is limited in its ability to conduct availability and sustainability analyses of time-varying operational demands, which are crucial in Operations & Support (O&S) and contingency planning. As the RSAF seeks expansion in its force structure to include more sophisticated weapon systems, the operating environment will become more complex. Agile and responsive logistics solutions are needed to ensure the RSAF engineering community stays abreast and consistently push for deepening competencies, particularly in LSA capabilities.

This research is aimed at the development of a model solution that combines spares optimization and sustainability capabilities to meet the dynamic requirements in O&S and contingency operations planning. In particular, a unique dynamic operational profile conversion model was developed to realize these capabilities in the combined solution. It is envisaged that the research effort would afford the ease of use, versatility, speed and accuracy required in LSA studies, in order to provide the necessary edge in inventory reparable spares modeling.

This thesis is dedicated to my Wife and soon to be born Son for their patience and understanding throughout my time at the Air Force Institute of Technology.

Acknowledgments

My most sincere thanks go to my family for their patience and understanding throughout my AFIT experience, but especially for the many endless hours I spent developing this research. Also, I would like to express my gratitude to Dr. Alan Johnson for his valuable guidance, complete trust and autonomy shown to me, without whom I could not have imagined putting this research together in a short span of time. Likewise, I would like to acknowledge my thesis reader, LtCol. (Dr.) Joseph Huscroft, for his frequent and pertinent advice throughout my research and coursework in AFIT. In addition, I wish to acknowledge the friendship and hard work of my fellow logistics management students, who have made my journey this one year all the more meaningful. Finally, I would like to thank my colleagues in both Air Engineering and Logistics Department and Defence Science & Technology Agency who provided the valuable support which I so crucially required in the course of this research.

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List of Acronyms

AAM:	Aircraft Availability Model
AELO:	Air Engineering and Logistics Organization
Ao:	Operational Availability
ASM:	Aircraft Sustainability Model
Bin:	Binomial
CE:	Cost-Effectiveness
D:	Depot
DSTA:	Defence Science & Technology Agency
DYNA-METRIC:	Dynamic Multi-Echelon Technique for Recoverable Item Control
EBO:	Expected Backorder
EOQ:	Economic Order Quantity
ERP:	Enterprise Resource Planning
FH:	Flying Hours
FMS:	Foreign Military Sales
GRG:	Generalized Reduced Gradient
HQ:	Headquarters
I:	Intermediate
ILS:	Integrated Logistics Support
LCM:	Life Cycle Management
LD:	Local Depot
LI:	Local Intermediate
LRU:	Line Replaceable Unit
LSA:	Logistics Support Analysis
METRIC:	Multi-Echelon Technique for Recoverable Item Control
MOD-METRIC:	Modified Multi-Echelon Technique for Recoverable Item Control
MSD:	Mean Supply Delay
MTBF:	Mean Time Between Failure
MTTR:	Mean Time To Repair
Neg Bin:	Negative Binomial
NLP:	Non-Linear Programming
O:	Operational
O&S:	Operations & Support
OD:	Overseas Depot
OEM:	Original Equipment Manufacturers
OID:	Operational, Intermediate and Depot
OPUS10:	Optimization of Units as Spares
OST:	Order & Ship Time
PLT:	Procurement Lead Time
PM:	Preventive Maintenance
QPNHA:	Quantity Per Next Higher Assembly
RAMS:	Reliability, Availability, Maintainability & Supportability
RLT:	Repair Lead Time
RSAF:	Republic of Singapore Air Force

SRU:	Shop Replaceable Unit
SSRU:	Sub-Shop Replaceable Unit
TAT:	Turnaround Time
TPTA:	Third-Party Technology Transfer Agreements
UR:	Utilization Rate
USAF:	United States Air Force
V&V:	Verification and Validation
VARI-METRIC:	Variance Multi-Echelon Technique for Recoverable Item Control
VBO:	Variance Backorder
VTMR:	Variance To Mean Ratio
WF:	Weighting Factor
WUC:	Work Unit Code
WYSIWYG:	What You See Is What You Get

I. Introduction

Overview

This paper discusses Republic of Singapore Air Force inventory modeling of reparable spares. The Republic of Singapore Air Force (RSAF) conducts Logistics Support Analysis (LSA) studies in support of the various engineering and logistics efforts on the myriad of air defense weapon systems. Depending on the Life Cycle Management (LCM) phases of the weapon system, these studies can take the form of Reliability, Availability, Maintainability & Supportability (RAMS) front-end system definition analyses; and Maintenance Support Planning & Capability Generation analyses for Integrated Logistics Support (ILS) during Acquisition and Operations & Support (O&S) phases. In particular, spares provisioning, availability and sustainability are focus areas in LSA studies to optimize the support for weapon systems, spanning all phases of the LCM. This is especially crucial in an Air Force that operates with a relatively small force structure and heavily reliant on both Foreign Military Sales (FMS) and Original Equipment Manufacturers (OEM) for the continuous supply of aircraft spares to sustain fast changing operational requirements. In addition, the deterrence and diplomacy nature of the RSAF mission means that operational requirements manifest as planning parameters rather than real operations, and hence, grounded forecasting mechanisms play vital roles in resource optimization.

Because of the realities that the RSAF faces in the conduct of her missions, a comprehensive suite of commercial off-the-shelf software had been acquired over the years for performing the various LSA studies. Specifically, reparable spares inventory modeling is conducted through the Optimization of Units as Spares (OPUS10) software

(DISO, 2009:10-1 to 10-2). OPUS10 is a computer-based analytical software developed by Systecon®, a Swedish company with customers that include Defense Authorities in USA, Great Britain and Australia. It is an optimization software that uses a mathematical analytic model to analyze critical factors affecting a weapon system's availability and its associated spares build-up costs. The RSAF had been employing OPUS10 in many weapon system acquisition studies to primarily determine the optimum spares support package, given expected operating parameters and logistics & maintenance design plans on new induction platforms. Due to its extensive use in the RSAF, OPUS10 is also being employed during O&S phases to conduct regular reparable spares review and "top-up" purchases, complementing consumable spares Economic Order Quantity (EOQ) studies automated through the integrated SAP® Enterprise Resource Planning (ERP) information system of the RSAF. A more in-depth review of OPUS10 capabilities will be provided in the Literature Review chapter.

Problem Background

Although OPUS10 provides a compatible tool in acquisition settings where advance planning can be undertaken with detailed construction of the spares hierarchical structure, its performance is rather stretched in analyzing O&S phases of spares sustainment which warrants time-sensitive assessment of spares bottlenecks and the consequent effects on weapon system availability assessment. In particular, it is not well suited for analyzing multi-indenture and multi-echelon interactions of aircraft reparables and sensitivity analyses, which are evident in RSAF's O&S logistics structures, organized around Operational, Intermediate and Depot (OID) level maintenance systems. Moreover, the heavy reliance on OPUS10 over the years, results in curtailing of

fundamental competencies in spares reserve planning. Users become inapt to provide additional insights on effects of surge planning and supply chain constraints as a result of the limitations of the OPUS10 software. The author of this research had first-hand experience with operating OPUS10 and constantly faced the challenge to provide accurate and quick assessment of weapon system availability to decision makers in Exercise planning scenarios.

It became apparent that a novel solution that affords ease of use, versatility, speed and accuracy must be developed for studying spares optimization and sustainability in O&S planning and contingency operations. This forms the basis of the research problem.

Research Objectives

The intent of this research is to develop a model solution that affords ease of use, versatility, speed and accuracy in spares optimization and sustainability analyses conducted for O&S planning and contingency operations.

From the above main problem statement, three investigative questions were examined in this research:

(1) What model solution can be developed to combine ease of use, versatility, speed and accuracy for spares analyses?

(2) What model solution can be developed to conduct spares optimization and sustainability analyses for O&S planning and contingency operations?

(3) How can the developed model solution be validated for practical deployment?

Research Motivation

This research is timely as the RSAF seeks expansion in its force structure to include more sophisticated weapon systems, such as the F-35 Joint Strike Fighter. The Engineering and Logistics arm of the RSAF, the Air Engineering and Logistics Organization (AELO), must constantly seek agile and responsive logistics solutions in ensuring she meets the engineering demand of the Third Generation RSAF transformation ***(Ng, 2012:36)***. In addition, the roll out of the Military Domain Experts Scheme ***(MINDEF, 2009:7)*** in the RSAF engineering community also meant a push for deepening competencies in all logistics career fields and it is opportune to fundamentally reshape expertise in functional areas like the RSAF Supply Chain Management. It is thus envisioned that the conduct of this research will not only ground supply chain material planners in their core competencies but also ensure that they are able to conduct swift, accurate and credible inventory spares analyses to support O&S and Exercise planning and hence expand expertise on operational spares planning on future operating concepts.

This paper explores the development of a model solution that affords ease of use, versatility, speed and accuracy in spares optimization and sustainability analyses conducted for O&S planning and contingency operations. First, a literature review provides an overview of the RSAF reparable repair cycle, outlining the limitations of OPUS10 in the conduct of LSA studies. The review will also cover fundamental inventory METRIC models in use in other military establishments to build the foundation for development of the unique model solution. A description of the solution methodology will then be discussed, followed by an analysis of the results of model

development, verification and validation. Finally, recommendations for implementation of the model and avenues for further research will be presented.

II. Literature Review

RSAF Reparable Repair Cycle

Operational, Intermediate and Depot (OID) Levels Maintenance Support Concepts are documented in Air Force Logistics Orders ***(AELO, 2012:1-4)*** and the Singapore Ministry of Defence Life Cycle Management Manual ***(DISO 2009:5-1 to 5-5)***. Such concepts describe the inter-relationships of repair processes of RSAF's organic operational (O) level Line Replaceable Units (LRUs) and intermediate (I) level Shop Replaceable Units (SRUs), and strategic contractor's depot (D) Level Sub-Shop Replaceable Units (SSRUs). Figure 2-1 depicts a typical maintenance support scenario:

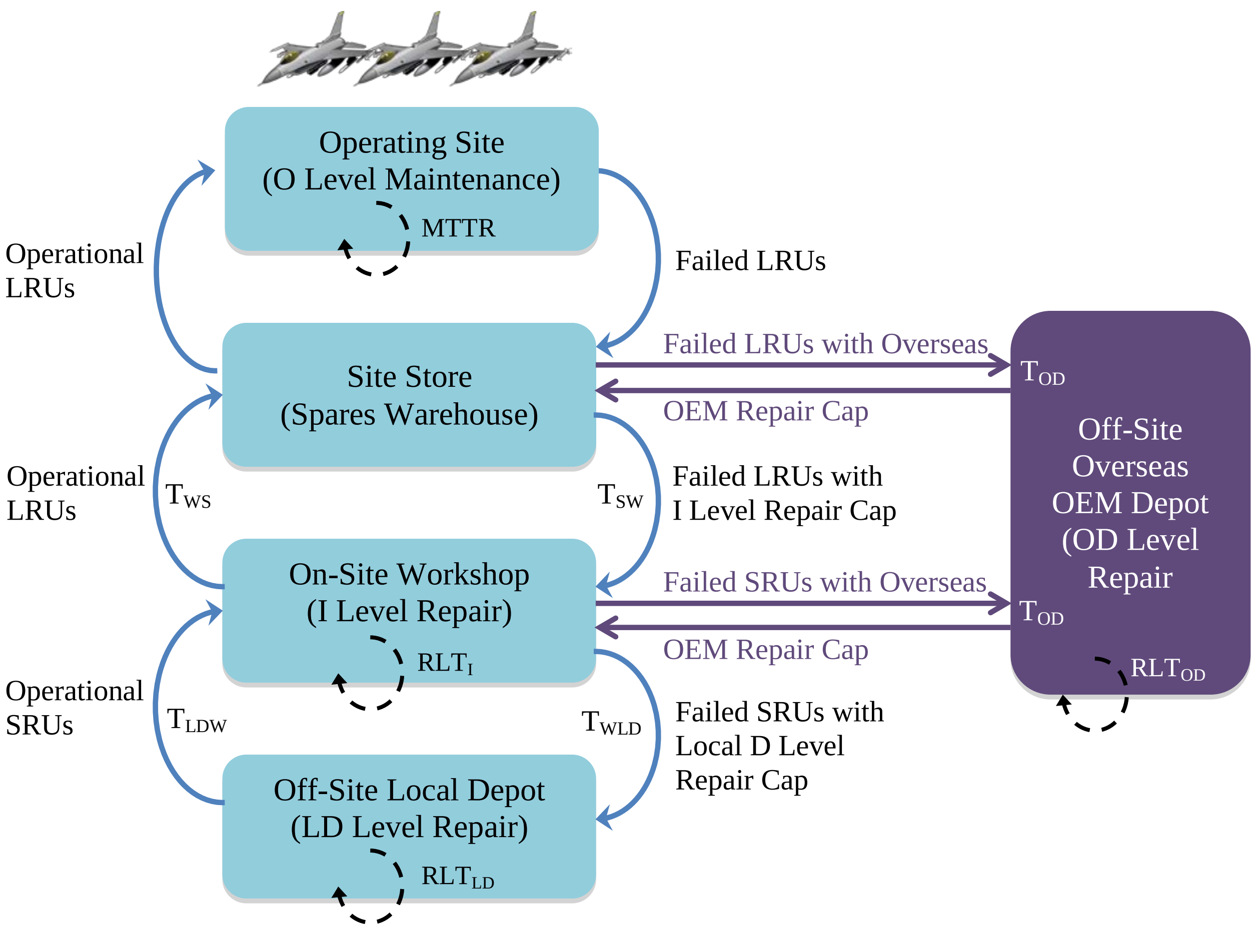


Figure 2-1. RSAF Reparable Maintenance Support Scenario

With reference to Figure 2-1, each operating site (air base) has several weapon systems (aircraft), the use of which generates LRU failures and thus demands for replacement components. Each site has its own aircraft repair crew that removes and replaces failed LRUs based on an average Mean Time To Repair (MTTR), inclusive of the time it takes for drawing serviceable spares from the site store. A spare LRU is issued if one is on hand, else a backorder is established.

A failed LRU enters the pipeline network when it is sent from the store to either the on-site workshop for I level repairs or to the OEM for Overseas Depot (OD) repair, based on the maintenance capability designated for the LRU. For LRU with I level repair capability only, the associated turnaround time (pipeline time) comprises both shipment times from store to on-site workshop (T_{sw}) and from on-site workshop back to store (T_{ws}), plus the repair lead time (RLT) of the I level workshop (RLT_I). While for LRU with OD repair capability only, the turnaround time comprises the shipment time to and from the OEM (T_{OD}) and the agreed contractual RLT (RLT_{OD}).

During the process when a failed LRU is repaired in the on-site workshop, a second-indenture, SRU is identified as having failed. If a spare SRU is available in the workshop, the failed SRU is removed and replaced by the workshop repair crew and the LRU repair is completed, otherwise an SRU backorder is established at either the strategic contractor Local Depot (LD) or the OEM for OD repair, depending again on the maintenance capability designated for the SRU.

The weapon systems supported by the store constantly generates demands that consume spares in the store. The average pipeline time translates to average pipeline size (average lead time demand) through the individual component failure rate (that is,

demand rate). This pipeline size describes the total number of LRUs or SRUs that have left either the on-site store or workshop for repair but have not returned from the respective repair agency. AELO uses this concept in its spares acquisition programs to define peacetime requirements for weapon system induction ***(DISO, 2009:10-1)***.

OPUS10

OPUS10 (Optimisation of Units as Spares) is a steady-state Logistics Support Analysis (LSA) software designed to calculate optimized cost-availability of spares and their distribution in the maintenance support organization ***(Systecon AB, 2007:1-4)***. An operational scenario with aircraft deployment, utilisation profiles and logistics stations (stores, workshops and depots) is modeled to establish a joint pattern of demand for logistics support. Maintenance and logistics activities (e.g. failure rate, inventory support concept) are also modeled. With this information, the software outputs optimal spares packages to support different required operational availability (Ao). This optimal spare package is a result of the "best-possible" relationship between cost and operational availability.

Central to the OPUS10 model is an analytic stationary Poisson process model. The computations are based on evaluating the pipeline sizes of the components given the maintenance structure, operational demands and average failure rates. These pipeline sizes translate to expected backorders and an optimization is performed to trade-off between Ao and cost of spares to produce a Cost-Effectiveness Curve as shown in Figure 2-2:

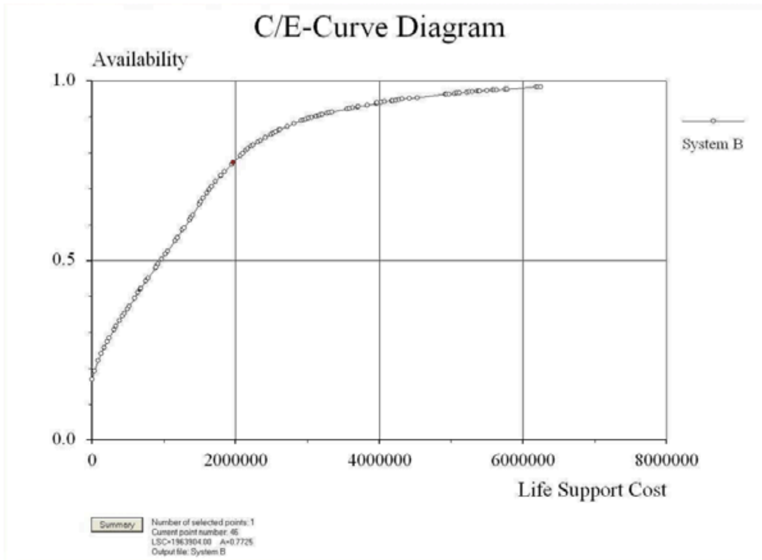


Figure 2-2. OPUS10 Sample Cost-Effectiveness (Availability vs Cost) Curve

OPUS10 modeling concept is purely analytical and requires stationary operational demand parameters. While this ensures LSA studies can be easily and quickly computed, it is rather limited in its ability to model highly varied operational demand patterns (for example, frequently changing flying profiles in contingency operations). In addition, the highly customized graphic user interface also meant that the optimization engine behind OPUS10 modeling is completely hidden from the user. While this takes away the mathematical woes of the analyst, it results in curtailing of competencies in understanding the fundamentals behind the model, which is key when conducting sensitivity analyses of changes of logistics variables often encountered in O&S and contingency operations. In addition, the speed afforded by OPUS10 is only as good as the run time and much attention is instead spent in constructing the model inputs. The author of this research collated data for a prior study in 2009 and determined a 90 minutes average requirement for conducting an OPUS10 LSA analysis:

Category	Sequential tasks for a single analysis	Time Required (mins)
Data Entry	Collate and manipulate input data in Excel	15
	Convert input data to software input format	30
Modeling	Create / Modify existing software's operations and logistics profile model	25
	Input of data into OPUS10 software	10
Results Output	Generate run results	5
	Analyze results	5
	Total Time Required	**90 mins**

Table 2-1. Time Required in OPUS10 LSA Studies

Another limitation of OPUS10 is its (s-1, s) inventory model for reparables. Although this is well suited for modeling low demand, high cost LRUs and SRUs, it may not accurately represent the high demand and low cost SSRUs. This is apparent in AELO case where current inventory policies do not spell out the modelling techniques for such items. OPUS10 was never designed for modelling these lower indenture items and an Economic Order Quantity (EOQ) model may perform better to implement a reorder point, order quantity (R, Q) policy for SSRUs. Finally, the Poisson process assumption used by OPUS10 postulates all components fail at random, with a Variance-to-Mean-Ratio (VTMR) of 1. This may not accurately represent in-service reparables which commonly fail due to wear-out (VTMR < 1) or due to reliability deterioration (VTMR > 1) ***(Adams et al., 1994:7 and 26-27; Sherbrooke, 2004: 62-63, 89-91)***.

Notwithstanding the limitations, this research will build upon the strength of the analytical methodology of OPUS10 to harness its concept of ease of use and speed, while

negating the limitations by revisiting the fundamentals in reparables inventory modeling and modifying the baseline concept for more accurate and versatile model development.

METRIC Models

The mathematical concepts behind OPUS10 can be traced to the Multi-Echelon Technique for Recoverable Item Control (METRIC) ***(Sherbrooke, 1968: 122-141)***. METRIC is a base-depot supply system model that calculates the optimal (s-1, s) stockage level for LRU items at each of several bases and the supporting depot. It utilizes the concept of minimization of the base backorders in relation to the demand patterns in both the base and the depot. This results in a systems level approach to stocking spares by analyzing the relation between backorders and system availability. A systems cost effectiveness curve is obtained by analysing the marginal benefit of increased availability from the next best option in spares purchase in terms of reduced overall system backorders ("bang per buck"). The METRIC model was a natural transition from Sherbrooke's prior work on the single indenture, single echelon Base Stockage Model ***(Feeney et al., 1965: 391-411)***.

Central to the METRIC model is the infinite channel queueing assumption of the Palm's Theorem ***(Sherbrooke, 2004: 22)***, which assumes demand for an item follows a Poisson process and that the probability distribution of the pipeline size is also Poisson. While this simplifies computations, item failure rates are consequently assumed to follow a VTMR of 1. However, this poorly models reliability deterioration and wear-out phenomena associated with aircraft components. This resulted in less than optimal prediction performance of the METRIC model, underestimating the items backorders leading to higher than observed operational availabilities and lower spare stockage levels.

The MOD-METRIC model ***(Muckstadt, 1973: 472-481)*** extended the multi-echelon base-depot supply to encompass analysis of multi-indenture systems (LRUs and SRUs) while retaining the stationary Poisson assumption. The complex dependencies from both the echelon and indenture structures further understate the backorders by nearly a factor of 4 ***(Sherbrooke, 2004: 67)***. Subsequent works from Gross, Graves and Sherbrooke ***(Gross, 1982: 1065-1079; Gross et al., 1983: 344-352; Graves, 1985: 1247-1256; Sherbrooke, 1986: 311-319)*** perfected the inventory modeling technique with the introduction of the VARI-METRIC model to generalize the stationary Poisson process to better model failure distributions described by the Binomial probabilities (for VTMR < 1) and Negative Binomial (for VTMR > 1).

The VARI-METRIC model afforded better accuracy with stock level deviation of 1 unit observed only in less than 1% of the case studies analyzed ***(Sherbrooke, 2004: 102)***. It was eventually adopted by USAF in the form of the Aircraft Availability Model (AAM) and is used for computing peacetime spares requirement ***(O'Malley, 1983: 1-3; Sherbrooke, 2004: 228; Blazer, 2007: 67-68)***. It became the benchmark inventory modeling technique, even till today, due to its robust modeling fundamentals and well documented mathematical solutions. However, it was strictly confined to peacetime spares modeling due to its requirement of a homogeneous Poisson process (that is, constant failure/demand rate). The concepts of VARI-METRIC were later modified into the Dyna-METRIC model to allow the conduct of wartime sustainability studies, which are characterized by varying periods of operational demands. Dyna-METRIC utilizes a dynamic form of Palm's theorem to effectively change the items' failure/demand rates based on planned changes to the flying profile. However, it is best described as an

assessment model rather than an optimization model and users have to first specify a level of spares and Dyna-METRIC determines the fleet availability that can be met with the planned flying intensities ***(Sherbrooke, 2004: 194)***. In addition, the adoption of a hazard rate $\lambda(t)$ instead of a constant failure rate λ also meant that the computations become rather complex for model development. The Dyna-METRIC was adopted by USAF in the form of the Aircraft Sustainability Model (ASM) and was extensively used in modeling contingency operations ***(Slay et al., 1996: 1-3 to 1-6, Sherbrooke, 2004: 194; Blazer, 2007: 68)***.

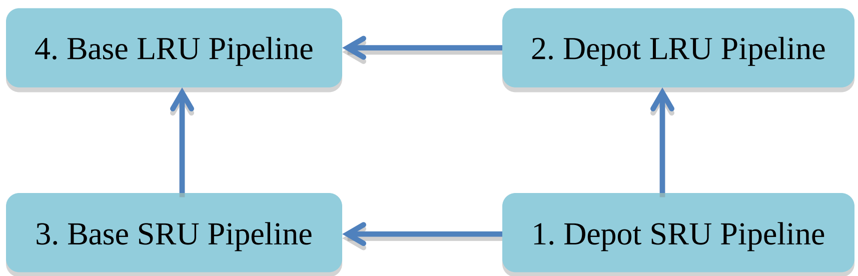
Perspectives of the Current Research

Given the insights of the RSAF reparable cycle, OPUS10 limitations and the foundations of the METRIC models, the current research can be aligned to develop a unique model solution, harnessing the advantages of the various perspectives and mitigate the limitations. To aid in the alignment, the investigative questions are analyzed to seek the best adaptation of the solution methodology:

(1) What model solution can be developed to combine ease of use, versatility, speed and accuracy for spares analyses?

The VARI-METRIC model, with its well-founded mathematical solutions, emerges as the best fit for tailoring the current research model solution. The ability to model stationary Poisson processes but yet generalized to handle failure rate variances, provide analytically tractable computations, which can be easily optimized in a spreadsheet non-linear programming (NLP) model. This will afford ease of use and speed for the solution. Versatility and accuracy of the model will depend on the

modifications of the VARI-METRIC to tailor to the unique RSAF context of reparable repair cycle. For this, the differences in repair pipeline depiction from the RSAF context need to be analyzed. The VARI-METRIC model is represented by the following visualization ***(Sherbrooke, 2004: 107)***:



(Arrows represent sequence of backorder computations)

Figure 2-3. VARI-METRIC Pipeline Visualization

Comparing Figure 2-1 and 2-3, two unique differences can be deduced. First, the VARI-METRIC model is tailored to the USAF mode of operations where LRUs and SRUs repairs are carried out by the Base or Depot depending on complexity of repair, whereas in the RSAF case, repair agencies are identified upfront for the different component types, and LRUs and SRU repairs are allocated distinctly to either local or overseas depot repair depending on the state of organic capability and standing third-party technology transfer agreements (TPTA) with the US Foreign Military Sales (FMS) Program and the respective OEMs. Second, the local depot capability (provided by commercial strategic contractor to the RSAF) was developed to solely focus on the repair of SRUs and a healthy level of SSRU stock is important to provide self-sustaining in-country capability, especially important during contingency operations where effects of

embargo are expected. As most SSRUs are low-cost, high demand items, their stockage policies cannot rely solely on backorder computations and a unique solution is required which favors concepts from a (R, Q) EOQ model.

Given the applicability of the VARI-METRIC model, the current research will employ this technique as the basis of the model, while designing modifications to accommodate the distinctiveness of the RSAF context. A spreadsheet model would be the main platform to deploy this optimization model given the strength of a "What You See Is What You Get" (WYSIWYG) interface[1]. This allows analysts to better appreciate the interactions between the model specifics and hence create the needed edge for conducting quick sensitivity analyzes ***(Seila, 2005: 34)***. This consequently assists to ground the necessary knowledge and expertise in inventory modeling, one of the main hurdles that limits OPUS10 usage in such settings.

(2) What model solution can be developed to conduct spares optimization and sustainability analyses for O&S planning and contingency operations?

VARI-METRIC was developed as a peacetime spare model and limited in its application for handling contingency analyses. Dyna-METRIC was more suitable but the complex modeling nature may impede the ease of use characteristics required of the research solution. If a novel approximate solution can be derived from the relationship of flying operational demands to other related factors, rather than failure rate changes

[1] "What You See Is What You Get" (WYSIWYG) is a computing concept popularized in desktop publishing design. It is extensively used in Web 2.0 design to create interactive web pages where the man-website interface is made to mimic desktop applications to enhance the user experience ***(Wolber et al., 2002: 228-229)***.

suggested by the Dyna-METRIC, the stationary Poisson process suggested by Palm's theorem can be retained for model simplicity, preserving the VARI-METRIC characteristics. This challenge will be a main focus area for the model development.

(3) How to ensure that the developed model solution is validated for practical deployment?

OPUS10 was a software solution that was constantly validated with real logistics operations in the RSAF. With that in mind, the research solution will be validated with OPUS10 to compare the output results. While OPUS10 may be limited in modeling versatility when compared to the objectives of this research, it is hypothesized that the validation results will be comparatively close since fleet availability is only a function of LRU backorders. In addition, if the proposed model is developed from a small subset of reparables, the compounding variances will not be too significant. These will ensure that the two platforms will be comparable in their respective models and valid conclusions from the results can be analyzed.

III. Methodology

This chapter documents the development of the unique solution models for analyzing the availability and sustainability of the RSAF reparable inventory. First, the conceptual flow of the model development will be constructed to guide the research effort. Second, valid assumptions that aid in aligning the focus of the model will be described. Third, the data requirement and collection for the model input will be expounded to form the basis of the analysis parameters. Fourth, the fundamental inventory modeling equations will be presented to provide a theoretical foundation for implementing the model. This will then guide the unique customization of the equations required for studying the RSAF reparable inventory concept. Subsequently, to tailor the model for both optimization and sustainability analyses, a novel solution will be developed to treat varying operational demand requirements to a form suitable for the analytical model. Finally, the development of the model solution will be explained through the steps necessary to chart out the analysis in a spreadsheet environment.

Conceptual Flow

Figure 3-1 details the conceptual flow of this research effort. Three distinct development phases will help guide the process of model development. First, in the 'Definition' phase, the fundamental inventory equations are visited to make sense of their applicability to the RSAF reparable maintenance context. In addition, the mechanics of dynamically changing operational demands will be examined to understand the variables that affect the utilization of spares in sustainability scenarios. These will aid in conceptualizing the principles behind the model solution. Concurrently, data collection

of both logistics and operational parameters will also proceed to facilitate the scanning of available information that will shape the model solution.

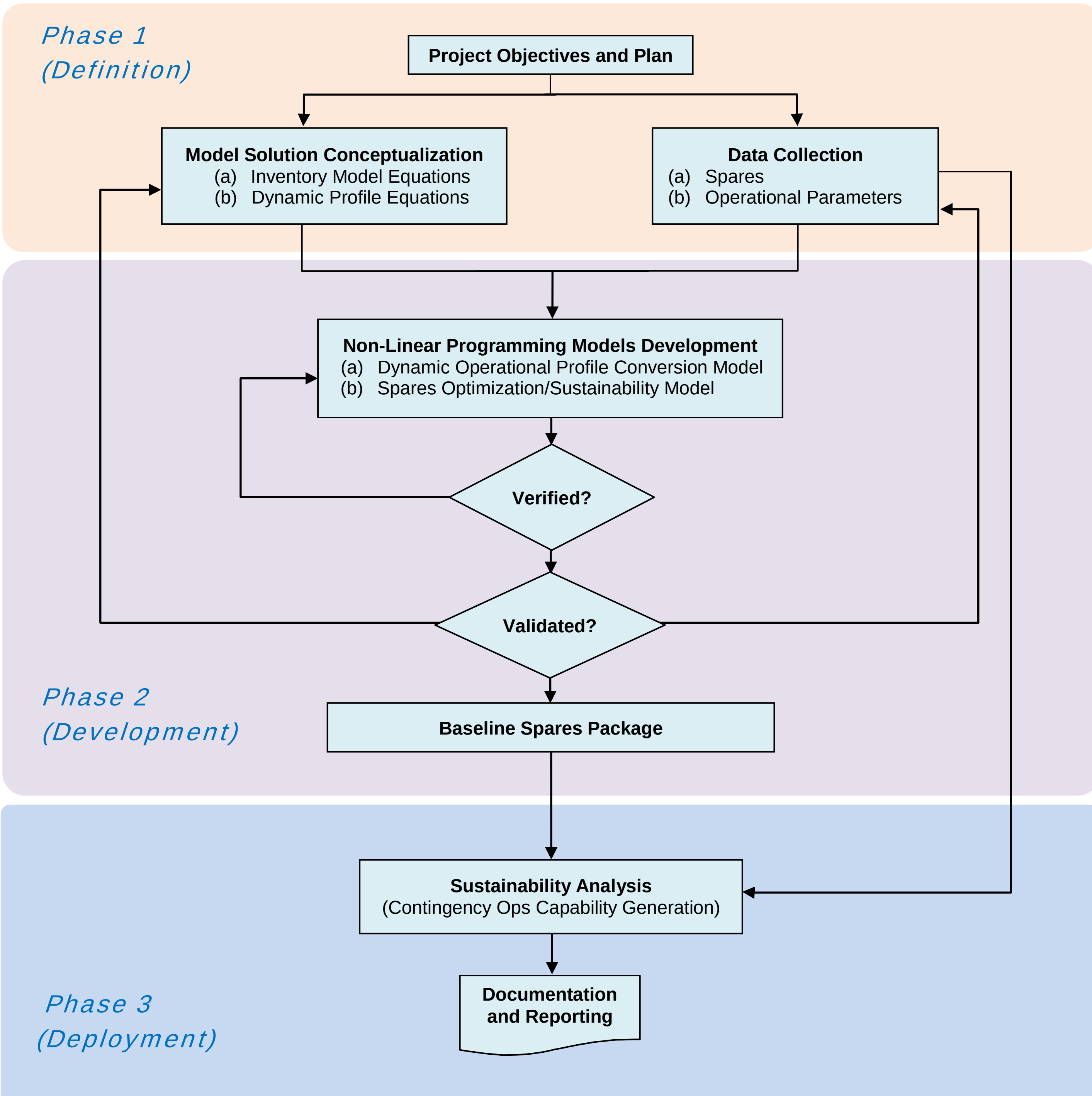


Figure 3-1. Research Conceptual Flow Chart
(Excerpted from ***Banks et al., 2010:34-39***)

Second, in the 'Development' phase, two models will be formulated to provide a combined solution to spares optimization and sustainability analysis. Initially, a dynamic operational profile conversion model will assist to analyze the effect of varying operational demands on system and logistics parameters and output these as modifiers to the inputs of the subsequent optimization/sustainability model. This latter model must furnish the provisions to analyze all levels of spares hierarchy, unique to the RSAF reparable repair cycle, and output an optimized spares package; and also be able to accept the changes in system and logistics parameters in order to afford the ability to conduct sustainability analysis. Verification and Validation will follow in the next chapter to compare the outputs from the developed model and an equivalent analysis obtained from OPUS10, so that insights can be obtained on the similarities and differences.

Finally, in the "Deployment" phase, the model will be used in sustainability analysis mode to gain appreciation of the performance of selected spares packages as they are deployed to support operations in a dynamic profile environment. The insights provided will translate to usable provisions for future sensitivity analyses. The research will then conclude on the recommendations for deployment of the developed model, re-visiting the assumptions to highlight the areas for improvement; and develop proposals for future research opportunities.

Assumptions

As many factors can influence inventory modeling, various assumptions are important to focus the research effort on the primary purpose of developing an optimization and sustainability tool. Some of the main guiding assumptions are:

(1) For operational inputs, this research is confined to the analysis of a typical fighter fleet operating in-country in one Air Base. Performance is analyzed to support an assumed operating profile and utilization.

(2) For logistics inputs, the scope will be confined to a representative set of reparable spares from critical aircraft mechanical and electrical sub-systems. To demonstrate the model applicability, these spares were chosen based on the myriad of possible repair capabilities (I, LD and OD cap) associated with the maintenance support context of the RSAF. In particular, depot level SSRUs are confined to a subset of propulsion spares to provide an indicative analysis of the LD echelon.

(3) Direct costs of spares are key focus of the study and indirect costs (e.g. warehousing, forward deployment) are not considered. This ensures that only the main cost drivers are analyzed.

(4) Maintenance effects (cannibalization and manpower constraints) are not considered. Focus is on supply effects on availability.

(5) Spares are assumed pre-positioned in operating Air Base and lateral supply support from other Bases are not considered. This provides a conservative modeling approach, particularly applicable in contingency operations, where sufficient spares need to be catered to maintain “self-sustenance” mode.

(6) An (s-1, s) inventory policy is assumed for all LRUs, SRUs and OD SSRUs, which mean such items are assumed not batched up for repair (Poisson process) and scrapped units are replaced on a one-for-one basis. For the case of LD SSRUs where demand rates are sufficiently high and costs are

sufficiently low, the EOQ inventory policy model (R,Q) is more suited for replenishment considerations.

(7) Embargo conditions are assumed in order to model realistic effects in contingency operations. Hence, maintenance capability resides only in-country as a consequence, at the onset of the sustainability period (i.e. only I and LD repair caps exist for continuous resupply and OD spares are "discarded" when defective).

(8) For lack of field experimentation data, software validation with OPUS10 is employed to provide a substitute comparative measure of model performance.

(9) Failures are assumed independent. A defect associated with any component does not affect the failure probability of another component in the same aircraft sub-system or other sub-systems.

(10) Only corrective maintenance (CM) is assumed to affect overall system Ao performance. Owing to its inherent predictability and hence different stocking policies, Preventive Maintenance (PM) is not considered to have any effect on failure probabilities.

Data Collection

Data needed for this research project is primarily sourced with the assistance from AELO HQ. The subset of spares was selected on the premise that they exhibit indicative wear-out and reliability deterioration phenomena. On this note, the aircraft sub-systems considered are propulsion, fuel, hydraulic, flight control and weapon delivery systems. In particular, the propulsion sub-system was expanded to include SSRUs. Spares information are extracted from the RSAF ERP system and include:

(1) LRU, SRU and SSRU hierarchy family tree and maintenance allocation chart.

(2) Work Unit Codes (WUC) of the Work Breakdown Structure of sub-systems.

(3) Mean Time Between Failure (MTBF) of individual spares and average Mean Time To Repair (MTTR) duration of AELO's maintenance efforts.

(4) Spares information – Quantity Per Next Higher Assembly (QPNHA), Cost (USD Million), Stock Level, Procurement Lead Time (PLT)/ Inventory Holding Cost Rate/ Ordering Cost of SSRU and transportation times.

The duration of the data sources was based on a minimum three year peacetime period. Information on SSRUs was obtained from depot contract management staff. In addition, various correspondences with AELO support staff were also made to obtain expert opinions on realistic measures when information is not available or when confirmation of planning norms is needed. Detailed spares information is provided in ***Appendix A***. For operational planning parameters, flying hours (FH), sustainability period duration and deployment concepts are required. Due to the sensitivity associated with such data and since this research is essentially a proof of concept; surrogate values are assumed, indicative of the varying operational demand profile.

Fundamental Inventory Modeling Equations

The literature on inventory modeling focuses on the concept of backorder, pipeline and Ao computations ***(Sherbrooke, 2004: 19-41)***.

Backorder Equations

The Expected Backorder (EBO) equation is derived from the first central moment in probability theory and is shown in Equation 1:

$$EBO(S) = \sum_{x=s+1}^{\infty} (x - S)\, Pr(X = x) \tag{1}$$

where

EBO(S) is the expected backorder associated with the stock level *S* of an item

x is a discrete random variable

Pr (X = x) is the probability distribution of the variable *x*

Given a stock level and probability distribution, Equation 1 computes the predicted number of backorders in an inventory of reparables. For simplicity of computation, a closed form version of Equation 1 is shown below in Equation 2:

$$EBO(S) = \mu - S + \sum_{x=0}^{S} (S - x)\, Pr(X = x) \tag{2}$$

where

μ is the expected value or mean of the demand for an item with stock level *S*

Besides the EBO equation, key to this research is the Variance Backorder (VBO) equation, which supports the modeling of reparables that exhibit wear-out and reliability growth trends. From the second central moment, the VBO equation is shown below in Equation 3:

$$VBO(S) = E[B^2(X \mid S)] - [EBO(S)]^2 \tag{3}$$

where

$E[B^2(X \mid S)]$ is the second moment of the backorder = $\sum_{x=s+1}^{\infty} (x - S)^2\, Pr(X = x)$

$[EBO(S)]^2$ is the square of the Expected Backorder function

Three probability distributions are utilized in this research that best represent the variability of the backorders. The Poisson distribution is used extensively to model random failures ***(Sherbrooke, 2004: 21, Banks et al., 2010: 205)***. However, the current research is focused on modeling generalized Poisson failure processes that exhibit wear-out and reliability deterioration. For wear-out processes where demand rates increase around a service life, this can be conveniently represented by the Binomial distribution:

$$Binomial\ Pr(x) = \binom{n}{x} \rho^x (1-\rho)^{n-x} \qquad x = 0, 1, 2, \ldots, n \tag{4}$$

where

x is the number of successes in n trials, each trial with ρ success probability

$n = \mu / (1 - VTMR)$ (μ = mean of the demand, $VTMR$ = Variance-to-Mean Ratio)

$\rho = 1 - VTMR$

***VTMR* < 1** for Binomial distribution

For reparables that exhibit reliability deterioration over time, the VTMR tends to increase, consistent with a Poisson process with non-stationary increments. The Negative Binomial distribution can be represented in Equation 5:

$$Negative\ Binomial\ Pr(x) = \binom{a+x-1}{x} b^x (1-b)^a \qquad x = 0, 1, 2, \ldots \tag{5}$$

where

x is the number of failures, a is the number of successes, $x + a$ total trials

$a = \mu / (VTMR - 1)$

$b = (VTMR - 1) / VTMR$

***VTMR* > 1** for Negative Binomial

The current research will factor such probability distributions to include in the model so that provisions can be afforded to realistically represent the failure behaviors of aircraft reparables as opposed to the traditional Poisson random failure process.

Pipeline Equations

To determine the optimal spares level required, the proposed model must analyze the demand for spares generated by failures from aircraft utilization. This demand results in the need for replacement components, fulfilled from a spare pool. The defective components enter the repair cycle pipeline and it is the variability of this pipeline (size and turnaround time) that is the focus of inventory optimization. The pipeline size denotes the number of units of an item in repair at a site or being resupplied to the site from a lower repair echelon. It consists of 2 components, namely, the number of demands during the turnaround time (TAT) and the number of demands prior to the TAT awaiting a lower echelon item that is backordered and impedes the recovery of the higher echelon item. All METRIC models are founded on this fundamental notion of pipeline optimization. To illustrate, consider the case of a two-level indenture LRU/SRU pipeline represented by the following Equation 6:

$$E[X_0] = m_0 T_0 + \sum_{i=1}^{I} EBO(s_i \mid m_i T_i) \tag{6}$$

where

$E[X_0]$ is the expected pipeline size of a higher echelon reparable 0 (e.g. an LRU)

$m_0 T_0$ is the expected demand during the TAT of the LRU (where m_0 is the demand rate and T_0 the TAT)

$\sum_{i=1}^{I} EBO(s_i \mid m_i T_i)$ is the Summation of all Expected Backorders of *I* lower echelon reparables (i.e. SRUs) that make up the higher echelon LRU and this impedes the recovery of the LRU

Similarly, the dispersion around this pipeline expectation can be represented by the variance of the pipeline, represented by the following Equation 7:

$$V[X_0] = m_0 T_0 + \sum_{i=1}^{I} VBO(s_i \mid m_i T_i) \tag{7}$$

where

$V[X_0]$ is the variance of pipeline size of a higher echelon reparable (e.g. an LRU)

$\sum_{i=1}^{I} VBO(s_i \mid m_i T_i)$ is the Summation of all Variance Backorders of lower echelon reparables (i.e. SRUs) that make up the higher echelon LRU.

Operational Availability (Ao) Equation

One of the advantages in deploying the METRIC model is its ability to aggregate supply stocking analysis to Ao computations ***(Sherbrooke, 2004: 2-3, 14-17)***. It provides a system approach to associate a direct relationship between the stocking decision and the effect on overall system performance. The decision to expense budget on the type and level of spares to purchase could have been easily resolved on an item approach, but it is the translation of the METRIC model to system performance that affords the edge to

decision makers on the cost-effectiveness dimension. The Ao equation that will be employed in this research is shown below in Equation 8:

$$Operational\ Availability\ (Ao\,\%) = \left(\frac{100 * MTBF}{MTBF + MTTR + MSD} \right)_{system} \tag{8}$$

where

MTBF = System Mean Time Between Failure

MTTR = System Mean Time to Repair

MSD = System Mean Supply Delay

In this research, we will only assume corrective maintenance affecting overall system performance. Preventive Maintenance (PM) is inherently predictable and stocking of spares would have been pre-planned prior to the sustainability period. In addition, management decisions would have been focused to minimize the need for PM, but even if it is required during the sustainability period, it would have been carried out during lull periods and would not have much impact on Ao. The System MTBF can be analytically computed from the model, utilizing the Poisson pooled process assumption given by Equation 9:

$$MTBF_{system} = \frac{1}{\sum_{i=1}^{I} \lambda_i * QPNHA_i} \tag{9}$$

where

λ_i is the failure rate (i.e. demand rate) of the *ith* LRU

$QPNHA_i$ is the Quantity per Next Higher Assembly of the *ith* LRU

The System MTTR measures maintenance efficiency on the time required to repair and turnover an aircraft. In the sustainability period, manpower constraints are deemed sufficient so that planning norms on MTTR are usually assumed. The System MSD can be expressed in terms of backorders computation and relates the stocking levels of all LRUs to the expected down time that the system experiences due to the delay in spare availability. This is shown below in Equation 10:

$$MSD = OST + \left[MTTF * \sum_{i=1}^{I} EBO_i \right] \tag{10}$$

where

OST = Order & Ship Time (planning norm)

$\left[MTTF * \sum_{i=1}^{I} EBO_i \right]$ is the portion of the *MSD* that translates the total expected backorders of all *ith* LRUs into a time delay experienced by the system

To allow sustainability analysis to be conducted, the system Ao performance must be modified to include provisions for varying operational demands to effect changes to the availability computation. To achieve this, the concept of Aircraft Utilization Rate (UR) can be introduced. UR defines the intensity of operational demand (in terms of flying hours) on the system and this intensity changes in a varying operating profile imposed on the aircraft fleet. Equation 11 shows the definition of UR:

$$Aircraft\ Segment\ UR = \frac{Segment\ Flying\ Hours}{Segment\ Duration\ Hours\ *\ Number\ of\ Aircraft} \tag{11}$$

where

Segment Duration defines the duration of time of the individual segment that the aircraft fleet experiences different flying intensity.

Aircraft Segment UR is a unit-less quantity and is directly proportional to the intensity of flying experienced in the individual segments. A UR of 0.5 denotes an aircraft is airborne half the time in a particular time segment. This will be used to scale the System MTBF accordingly to reflect the impact of flying intensity in varying periods of operations on system behavior of failure tendency.

With the above equations, the overall Ao equation can be re-expressed as Equation 12:

$$\text{Operational Availability}\,(Ao\,\%) = \left(\frac{100 * [MTBF / UR]}{[MTBF / UR] + MTTR + OST + [MTBF * \sum_{i=1}^{I} EBO_i]} \right)_{system} \tag{12}$$

RSAF Reparable Pipeline Equations

Having analyzed the equations required for fundamental inventory modeling, it is timely to re-visit the RSAF context so that the computations can be customized in terms of demand rates, pipeline expected backorder and variance backorder evaluations. Both the demand and backorder computations are complimentary in their calculation sequence. With reference to Figure 2-1, Figure 3-2 summarizes this concept in the RSAF context:

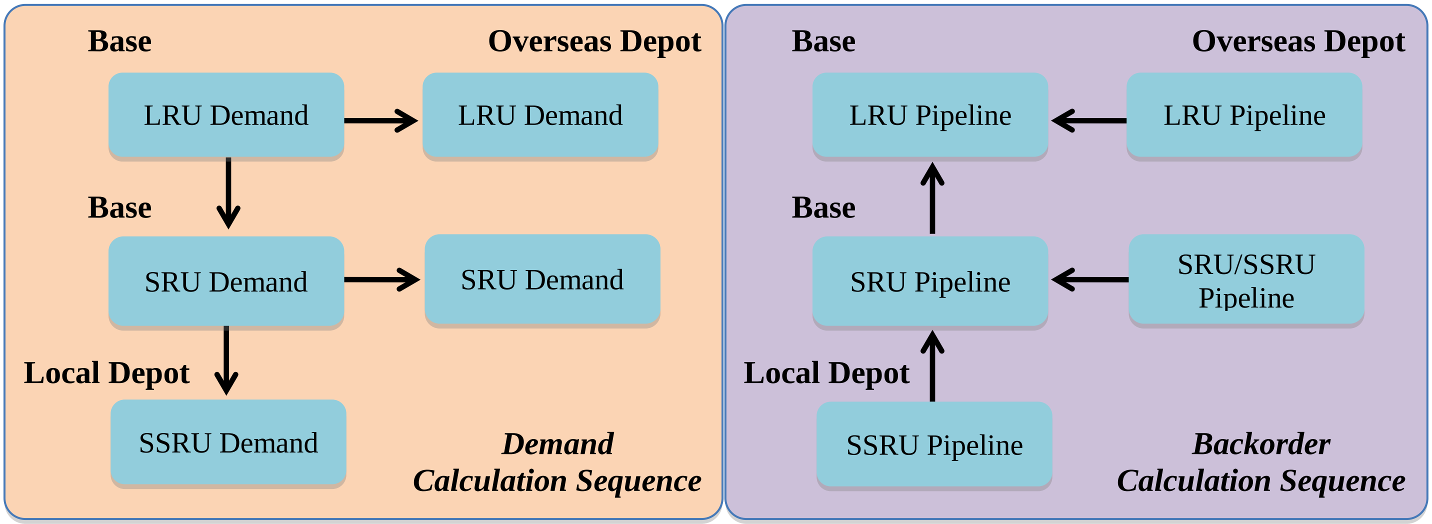


Figure 3-2. RSAF Reparable Calculation Sequence

Demand Rates

Based on the Poisson random splitting process (***Banks et al., 2010:34-39)***, the average demand rate for a lower echelon item, e.g. SRU *j*, is the average demand rate for the higher echelon item, e.g. LRU *i*, times the probability that the LRU repair results in a demand for SRU *i* and divide by the QPNHA for SRU *i*. The same relationship exists between the SRU and SSRU. The demand rate equation is given below in Equation 13:

$$Demand\ Rate\ (i.e.\ Failure\ Rate)\ m_i = m_0 r_i \,/\, QPNHA_i \qquad (13)$$

where

m_i is the demand rate of SRU_i

m_0 is the demand rate of the higher echelon LRU_0

r_i is the probability of demand for SRU_i when LRU_0 fails

$QPNHA_i$ is the Quantity per Next Higher Assembly of SRU_i

For the SRU/ SSRU relationship, the notation *i* is substituted by *j* to denote the SSRU and the notation *0* is substituted by *i* to denote the higher echelon SRU. In addition, the RSAF context calls for the complete separability of the various levels of item repair capability and this causes the mirroring of the OD demand rates from the Base to the Overseas Depot (OEM).

Mean and Variance of RSAF Repair Pipelines

With reference to Figure 3-2, the backorder computations start off at the lowest levels of the repair hierarchy. This consists of LRU, SRU and SSRU repair at the OD level and the SSRU repair at the LD level. At the OD level, the demand rate seen by the OEM is the “mirror” of the demand rates seen at the Base. As such, the pipeline size consists of both the demand during the TAT and the EBO of the affected part. Equation 14 and 15 detail the expected and variance pipeline sizes of these items:

For LRU OD repair:

$$E[X_0] = m_0 T_0 + \sum_{0=1}^{0} EBO(s_0 \mid m_0 T_0) \tag{14}$$

$$V[X_0] = m_0 T_0 + \sum_{0=1}^{0} VBO(s_0 \mid m_0 T_0) \tag{15}$$

For SRU OD repair, replace notation 0 with i and for SSRU LD and OD repair, replace 0 with j.

For Base LI repair of SRU and LRU, the dependency between the Base and LD repair cycle translates to pipeline sizes that must consider the backorder computations of the lower echelon items. As such, the pipeline computations will be different from Equations 14 and 15:

For LRU LI repair:

$$E[X_0] = m_0 T_0 + \sum_{i=1}^{I} EBO(s_i \mid m_i T_i) \tag{16}$$

$$V[X_0] = m_0 T_0 + \sum_{i=1}^{I} VBO(s_i \mid m_i T_i) \tag{17}$$

For SRU LI repair, replace notation 0 with i and notation i with j.

With the expected and variance pipeline sizes defined, the backorders are computed either through Equation 4 or 5 to first calculate the relevant probabilities and then applied to Equations 2 and 3 to obtain the expected and variance backorders respectively. Of note, the use of either Equation 4 or 5 depends on the ratio of the variance to mean pipeline size (i.e. the VTMR) – for VTMR < 1, Equation 4 invokes the Binomial distribution and for VTMR > 1, Equation 5 invokes the Negative Binomial distribution. Taken together, the EBO of a higher echelon item would be given by Equation 18:

$$EBO(s_0 \mid E[X_0], Var[X_0]) \tag{18}$$

That is, the Expected Backorder EBO of an item is a function of its spare level S_0, given an expected pipeline size $E[X_0]$ and a variance of pipeline size $V[X_0]$.

Unique treatment to the EBO computed for LD SSRU is required to cater the spare levels for these low cost, high demand items. Instead of a (s-1, s) inventory policy, a (R, Q) EOQ model is more appropriate to define an item approach for stocking these items. Fortunately, the EBO computed for these items can be used to approximate the stocking levels required ***(Sherbrooke, 2004: 19-41)***. The EOQ is given in Equation 19:

$$Q = \frac{\sigma}{2} + \sqrt{\frac{2(FC)m}{(IC)(UC)} + \frac{\sigma^2}{2}} \tag{19}$$

where

Q = Ordering quantity FC = Fixed Ordering Cost

σ = Standard deviation of demand over a lead time = $\sqrt{m * PLT}$

m = demand rate per hr PLT = Procurement Lead Time (hrs)

IC = Inventory Carrying Cost Rate (per unit per \$) UC = Item Unit Cost

The re-order quantity R can be resolved in Equation 20:

$$R = \mu + k\sigma = (m * PLT) + \left(-\frac{1}{\sqrt{2}} \ln \frac{4Q(EBO_j)}{\sigma^2 \left(1 - e^{-\frac{\sqrt{2} * Q}{\sigma}} \right)} \right) * \sigma \tag{20}$$

As such, the SSRU LD EBO_j enters the computation to influence the re-order quantity R.

Dynamic Operational Profile Conversion Model

The computation given by Equation 8 allowed the coupling of the relationship between Ao and MSD (hence supply EBO). Equation 12 further extend the concept to provide the ability to study varying period of flying intensities by including UR to scale the System MTBF. At this juncture, the research had since set up the provisions for both optimization and sustainability analyses (i.e. the “what”). It is now crucial to evaluate the impact of how these varying intensities affect the provisions (i.e. the system behavior) to derive the computational data input for model optimization and sustainability analyses (i.e. the “how-to”).

Optimization Analysis Treatment

From Equation 12, the variables that will change with time periods of varying flying intensities will be UR and EBO. Furthermore, EBO can be seen to vary with $E[X_0]$ and $V[X_0]$ in Equation 18. Tracing these to Equations 14 and 15, the pipeline sizes are a function of both the demand rate (m) and turnaround time (TAT). As mentioned previously, varying the demand rate m was the central focus behind the Dyna-METRIC model but it would be difficult and complex for the current research model to define hazard rates $m(t)$, while at the same time deploy a model that is easy to use and quick in computation. As such, we will derive the relationships between Ao and UR and between UR and TAT as the focus of this research to enable the model to breakdown the effect of varying flying profile.

Utilization Rate Effects

UR vs Ao

The effect of UR on Ao can be demonstrated through an example. Suppose a sustainability period with 3 distinct segments of flying intensity and the following arbitrary figures for computation of Ao:

System MTBF = 200 hrs *MTTR = 2 hrs* *OST = 20 hrs*

EBO = 0 (i.e. infinite spares – chosen to isolate the effect of UR on Ao)

UR for Segment 1 = 0.5 *UR for Segment 2 = 0.8* *UR for Segment 3 = 0.3*

Using Equation 12, the various Maximum Achievable Ao in each segment are:

Ao for Segment 1 = 94.8% *Ao for Segment 2 = 91.9%* *Ao for Segment 3 = 96.8%*

Clearly, the minimum Ao achievable within the entire sustainability period is Segment 2 (91.9%) with the highest intensity (UR of 0.8). This implies that the model needs to consider the *UR of the highest intensity segment as the input for the optimization phase* in order to cater the spare level required to sustain the segment with most spares requirement. This is in consideration that EBO will never be zero and its inclusion into the above example will further reduce Ao.

UR vs LI/LD TAT

Turning the attention to UR effects on TAT, we will first examine the case of LI and LD TATs. Often, these TATs are shorter than the duration of the entire sustainability period and they change from longer peacetime planning norms to shorter surge duration when maintenance efforts intensify from segment to segment. To illustrate the characteristics of TAT changes within the sustainability period, consider the same example, where:

System MTBF = 10 hrs (Demand Rate = 1 / 10 per hr)

EBO = 0 (i.e. infinite spares – chosen to isolate the effect of UR on TAT)

UR for Segment 1 = 0.5 *UR for Segment 2 = 0.8* *UR for Segment 3 = 0.3*

TAT for Segment 1 = 168hrs *TAT for Segment 2 =72 hrs* *TAT for Segment 3 = 72 hrs*

If Equation 14 is modified to compute the relative pipeline size of each segment, i.e. *Pipeline Size* $= UR * m_0 * T_0$, then:

Pipeline Size for Segment 1 = 8.4

Pipeline Size for Segment 2 = 5.8

Pipeline Size for Segment 2 = 2.2

It is observed that the largest pipeline size occurs in Segment 1, however this does not coincide with the segment with the highest UR. Previously, it was determined that the UR of the highest intensity segment will be used as input in optimization studies, but if its corresponding TAT is used (in this example 72 hrs in Segment 2), the optimization output would under-estimate the level of spares. Hence, a weighting factor (WF) based on the relative UR would need to be applied to scale the TAT in the highest intensity segment as a function of the TAT in the max pipeline segment. As such, this weighting factor is defined below in Equation 21:

$$Weighting\ Factor\ (WF) = \frac{UR_{Max\ Pipeline\ Segment}}{UR_{max}} \tag{21}$$

and the weighted TAT:

$$(LI/LD\ Item\ TAT)_{Highest\ UR\ Segment} = WF * (Item\ TAT)_{Max\ Pipeline\ Segment} \tag{22}$$

Through Equations 21 and 22, a relationship between UR and LI/LD TAT is derived. Of note, if WF equals 1 when the max pipeline segment is also the highest UR segment, there will be no change in the TAT value and the computation would be based exactly on the UR and TAT parameters experienced in the highest intensity segment.

UR vs OD TAT

OD TATs, unlike LI/LD TATs, are often longer than the sustainability period due to the lead-time of OEM repair and the possibility of embargo conditions. OD items can be viewed as "non-reparables", discarded as failures occur in the sustainability period. Therefore, the OD TAT should reflect the duration of utilization of the system over the sustainability period. However, since UR is different in different segments, an average

UR is first computed over the entire period and then weighted with the Max UR to obtain an approximation of OD TAT. This is shown in Equation 23:

$$UR_{average} = \frac{\sum_{k=1}^{K}\left(UR_{Segment\,k} * Duration_{Segment\,k}\right)}{Total\ Sustainability\ Period\ Duration} \tag{23}$$

Then the weighted OD TAT is:

$$(OD\ Item\ TAT)_{optimization} = \frac{UR_{average}}{UR_{max}} * Total\ Sustainability\ Period\ Duration \tag{24}$$

Sustainability Analysis Treatment

The optimization analysis will output a baseline spares package to support operational requirements in the segment with the highest UR. The prior UR modifications are focused on weighting the various TATs to approximate the conditions for spares provision. However, for sustainability analysis, the performance of this spares package need to be imposed with the "true" planning norm TATs that are stated in current logistics policies. This would mean *LI/LD Original TATs planning norms will be used at the various segments* to perform the sustainability analysis using the same optimization model, while holding the baseline spares at the level defined in the prior optimization phase. The problem is with OD TAT, since planning norms cannot be used in this respect, as their duration is often more than the duration of the entire sustainability period. The OD TAT in sustainability analysis in every segment can be viewed as the cumulative elapsed time in the sustainability period weighted to the utilization seen by the system in the current segment:

$$(OD\ Item\,TAT\,)_{sustainability\ segment\ K} = \frac{\sum_{k=1}^{K}\left(UR_{Segment\ k} * Duration_{Segment\ k}\right)}{UR_{Segment\ K}} \tag{25}$$

The denominator in Equation 25 weights the total elapsed time seen by the system (the numerator) by what is seen in that particular segment of analysis. Equation 25 is different from Equation 24 as it computes the elapsed OD Item TAT in each segment, whereas Equation 24 computes the OD Item TAT seen by the system in the entire sustainability period (inclusive of all segments).

Non-Linear Programming (NLP) Model Development

The various equations developed will now be laid out in a spreadsheet model, in a form suitable for both optimization and sustainability analyses. The objective is to ensure a WYSIWYG interface so that analysts are able to appreciate all the interactions between the model specifics and hence better positioned to conduct quick sensitivity analyzes (one of the main impetus for this research). This section will explain the model development by stepping through the process necessary for deployment of the model as it would be done in actual implementation of any optimization and sustainability studies.

Step 1: Collect the Spares Data according to the format detailed in ***Appendix A***.

Step 2: Logistics parameters (RLT, OST, PLT, etc.) are collected and combined with the Spares information in a form excerpted in ***Appendix B***.

Step 3: Operational parameters (Segment Duration, Segment FH, Operational Assets, etc.) are collected and input to the Dynamic Operational Profile Conversion Model (***Appendix C***) to compute the various optimization and sustainability analysis modeling

parameters (Segment & Weighted TATs, Segment & Max UR, etc.). For this research, operational parameters are arbitrary assumed figures.

Step 4: Compute items' backorders based on the level of spares hierarchy defined for the individual spares (i.e. expected & variance pipelines, expected & variance backorders of different permutations of Repair Cap (LI, LD or OD); and spares hierarchy (LRU, SRU or SSRU)). An excerpt of this computation is provided in ***Appendix D***. To aid in the automation of the computations, Excel VBA® Macros were written to define the applicable EBO computations (i.e. Poisson, Binomial and Negative Binomial). The programming scripts are detailed in ***Appendix E***.

Step 5: Compute the Spares Optimization and System Performance Measures (System MTBF, Cost of Spares and Ao) through setting up a NLP Model. The NLP logic is provided in ***Appendix F***. Microsoft Excel add-in Solver® tool is utilized to formulate and compute the spares requirement.

Step 6: With the baseline spares package optimized, input the sustainability analysis individual segment parameters (Original Segment UR, Original Segment LI/LD TATs and Weighted Segment OD TAT) into the same optimization model to compute the System Performance Measures in individual segments. This is done with the individual items' spare levels held at the quantity that were optimized at the required Ao.

IV. Results and Analysis

This chapter documents the results and analysis of the unique solution models developed in this research. First, the optimization's output is compared to a similar OPUS10 model output to verify and validate the model's performance in a Poisson case (where VTMR = 1). Second, the analysis of an optimization output from the model (with assumed VTMR) will be compared to the Poisson output to further validate the behavior of the Ao performance. Third, two baseline spares packages will be obtained from the model output and will be subjected to a sustainability analysis to evaluate the spares performance over an arbitrary selected period of varying flying profile. Insights will be deduced from the observations attained. Finally, overall model performance will be evaluated for its ability to combine ease of use, versatility and speed of analyses.

Verification and Validation

Model Setup

To conduct the Verification and Validation (V&V) phase of the model development, a varying operational profile is arbitrary chosen, imposed on a subset of aircraft sub-systems' spares. This is deliberately done in order to confine the research for proof of concept of the model. A four-segment sustainability period with the following parameters was chosen for the optimization and sustainability model:

Fleet Size: 40

Segment 1:	Duration = 1 month	UR = 0.0233
Segment 2:	Duration = 1 week	UR = 0.5
Segment 3:	Duration = 2 weeks	UR = 0.0372
Segment 4:	Duration = 1 week	UR = 0.0298

As mentioned, the spares information was selected based on the ability to exhibit failure wear-out and reliability deterioration characteristics. While the current RSAF ERP database do not capture the variances of MTBF and data collection in this respect would be manual down to component records, the current research will only arbitrary assume the figures particular to the nature of failure tendencies. The focus is to demonstrate the ability to model such parameters, given the necessary data input. For the sub-systems used in this model, the VTMR assumed are:

Propulsion, Fuel, Hydraulic components – VTMR = 0.75 [Wear-out tendency]

Flight Control, Weapon Delivery components – VTMR = 3 [Reliability Deterioration]

Detailed operational and logistics parameters are shown in Appendices A, B and C.

The NLP logic was setup with the use of Excel Solver® add-in. The Generalized Reduced Gradient (GRG) method was selected to resolve the NLP model. This method was chosen for its robust and reliable approach to solving non-linear problems (such as that presented in this research) as opposed to the Evolutionary method. Although one of the main limitations with the GRG method is its guarantee of only locally optimal solutions ***(Frontline Systems, 2010: 15)***, the accompanied Multistart technique to find a global solution casts too wide a solution space, hindering efficient run-time. A unique technique was engaged in this research to overcome this limitation by running the GRG method over 30 replications to obtain various local optimal solutions, enough for inference statistics to estimate the global solution; and by alternating these runs between spares cost increasing from 0 and decreasing from max budget, to ensure the obtained optima are independent indicators of the solution space. This technique not only estimates the probable global solution, but importantly, it conserves required run-time.

NLP and OPUS10 Models Comparison

Software validation was utilized to evaluate the NLP model performance. A Cost-Effectiveness (CE) curve from the NLP model was produced for comparison with an equivalent OPUS10 model output[2], a total of 2700 data points were captured over the 30 replications. As OPUS10 only produces a cost-effectiveness solution based on the Poisson pipeline assumption, the NLP model was modified to induce the same Poisson assumptions (i.e. VTMR = 1 for all sub-system components) for comparison. ***Appendix G*** details the results from both models. Figure 4-1 summarizes both model results in the form of a cost-effectiveness curve:

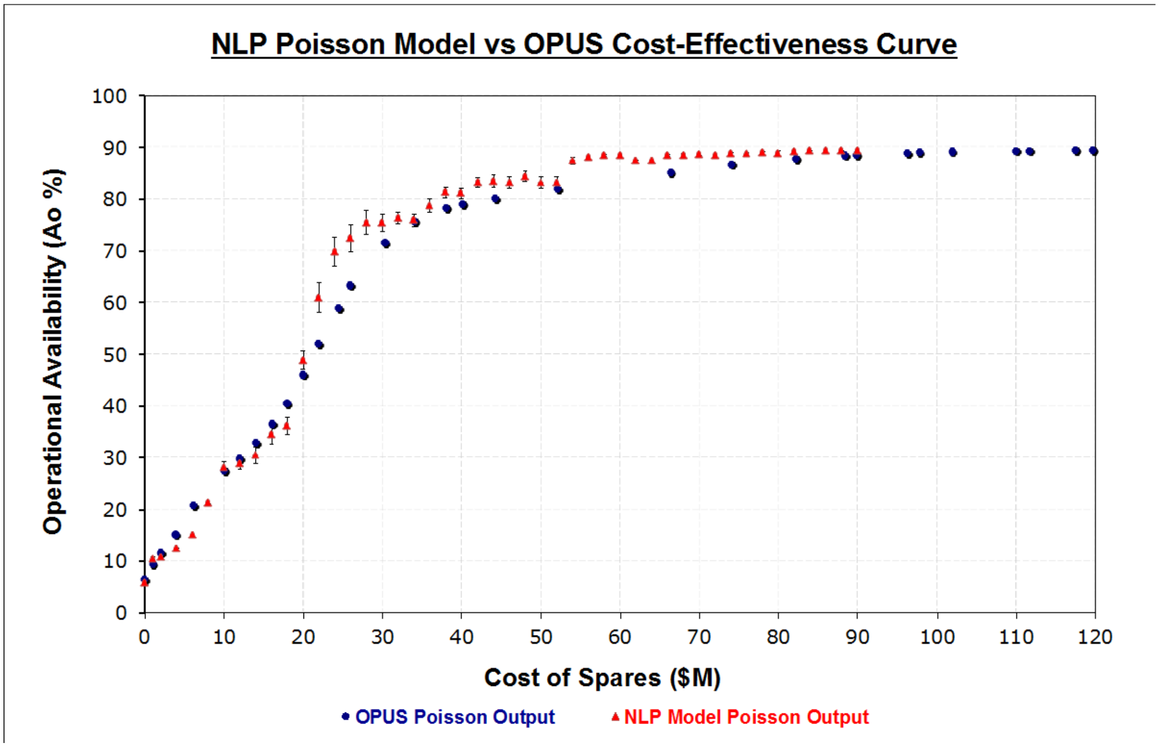


Figure 4-1. NLP Model vs OPUS10 Model Poisson Output

[2] An OPUS10 Model was developed with the assistance from AELO HQ and Defence Science & Technology Agency (DSTA) Systems Engineering Programme Centre. The OPUS10 results are detailed in ***Appendix H***.

With reference to Figure 4-1, various observations for validation can be deduced. First, the boundary conditions are justifiably validated at 6% initial Ao for no spares investment and at 89% when infinite spares are catered. Second, the NLP CE curve shows the same tracking behavior as the OPUS10 output, both Ao proportionately increasing with spares investment up till a diminishing region around 75 – 80% Ao. Third, in terms of tracking performance, the NLP Model was statistically indifferent (95% confidence interval and normally distributed) from the OPUS10 output from 0 – 40% and 85 – 89% Ao. Although the NLP Model is statistically different within the region of 40 - 85% Ao, the practical significant difference is not great, at around 5 – 10% from the OPUS10 output. Further evaluation of the spares output revealed that the Ao difference was due to the proposed stock level for the Engine LRU. The NLP model proposed 2 engines with accompanying reduced levels of SRUs and SSRUs, while the OPUS10 output proposed 1 engine with higher levels of the sub components. The NLP model was able to achieve this with a higher Ao and less cost investment. In addition, an emphasis to LRU stock is more advantageous in a sustainability setting since aircraft turnaround is vital in maintenance operations.

NLP Binomial/ Negative Binomial and Poisson Models Comparison

To further validate the model, the Binomial and Negative Binomial (Bin/Neg Bin) modeling capability was evaluated. Instead of VTMR = 1 for OPUS10 comparison, the various VTMRs assumed were utilized. With the majority of components at VTMR < 1 (i.e. 25 components out of 32 assumed VTMR = 0.75 and the remaining 7 components with VTMR = 3), the variability of the pipeline sizes is hypothesized to be smaller than

the Poisson case and therefore higher certainty that less spares would be needed for same Ao performance. The NLP outputs for this analysis can be summarized in Figure 4-2:

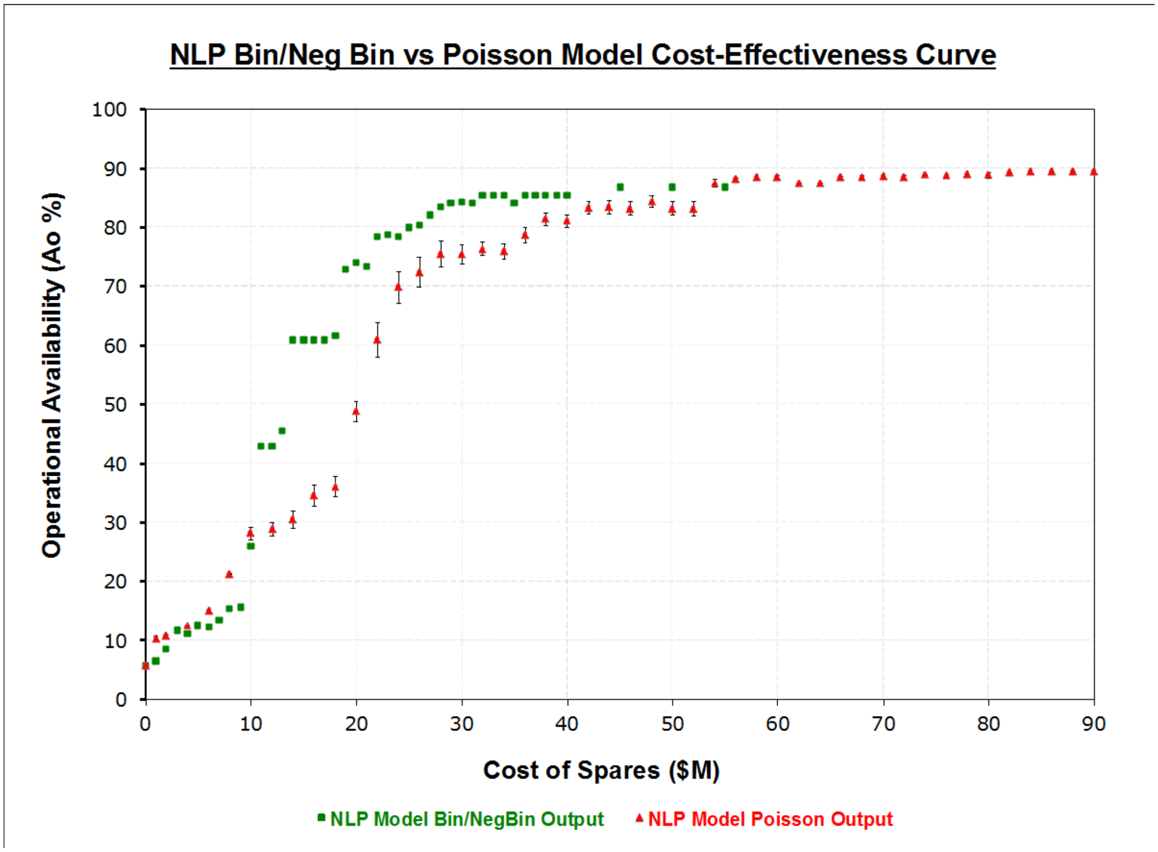


Figure 4-2. NLP Model Bin/NegBin vs Poisson Outputs

It can be observed that the less variability of pipeline sizes in the Bin/NegBin model results in a smaller budget needed for spares top-up to achieve a same level of Ao as the Poisson output. In addition, the saturation of Ao also happens at a lower budget in comparison to the Poisson model, further supporting the hypothesized behavior of the assumed model.

With all these observations, the developed model is sufficiently validated to model the failure behavior of aircraft sub-system spares. In addition, the model was able to achieve these outputs while conserving run time in a WYSIWYG spreadsheet

environment. We can conclude that the model is appropriately effective in its optimization capability.

Sustainability Analysis

In this section, the optimization capability of the model is translated to a form suitable for sustainability analysis to evaluate the performance of spares over the assigned segments' duration within the sustainability period. Referring to the previously obtained optimization output of the Bin/Neg Bin model, 2 optimization spares packages were chosen to demonstrate this portion of the model capability. Figure 4-3 shows the 2 spares package chosen for the sustainability analysis:

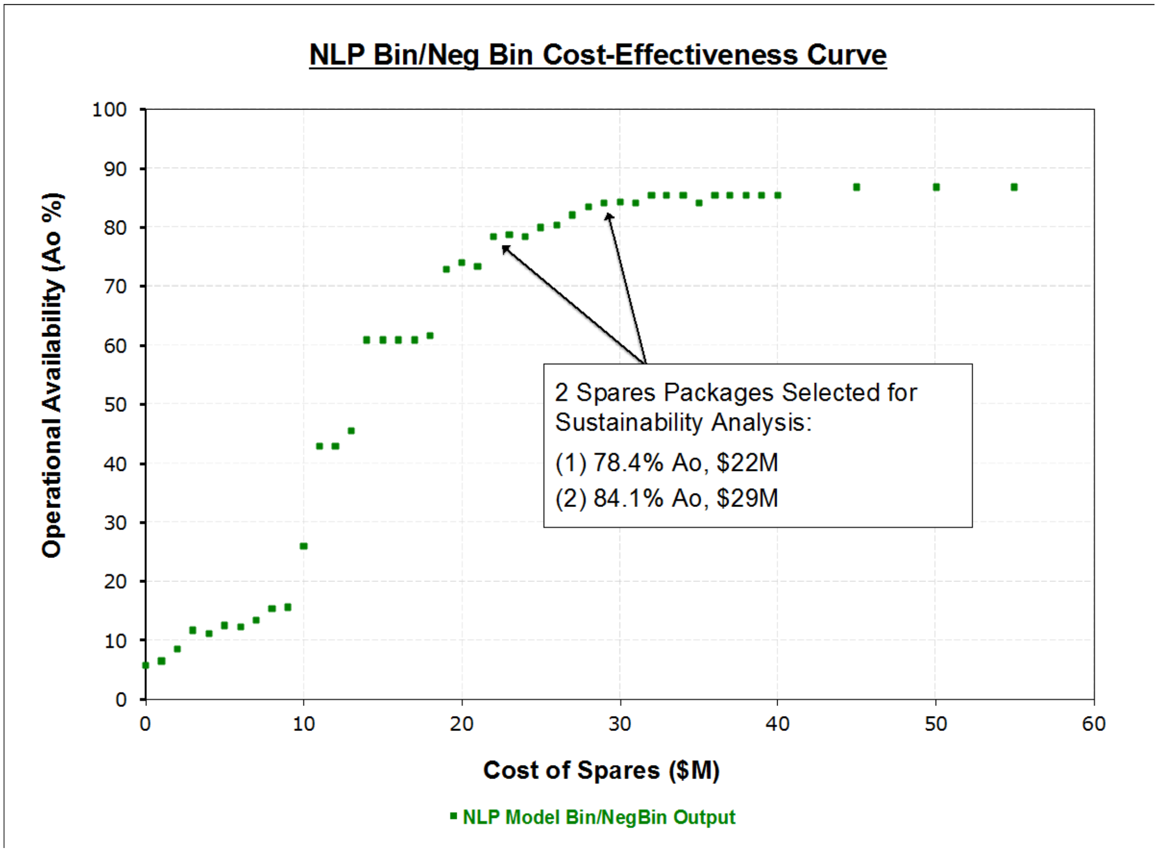


Figure 4-3. NLP Model Output for Spares Package Selection

The first package (78.4% Ao, $22M spares cost – henceforth referred to as *Package 1*) was selected as the most cost-effective spares mix at the end of increasing marginal returns. The second package (84.1% Ao, $29M spares cost – henceforth referred to as *Package 2*) was selected based on planning experience to ensure a certain level of fleet serviceability state but however may not be a cost-effective mix since it is within the region of diminishing marginal returns. These 2 spares packages were deliberately chosen to illustrate the sensitivity performance that the model affords to influence decision-making on spares acquisition.

The spares level for every component in each selected package is input to the model and the UR/TAT parameters computed in the dynamic operational profile conversion model for each segment is also varied to generate the Ao variation over the segments. The results from the analyses are summarized in Figure 4-4:

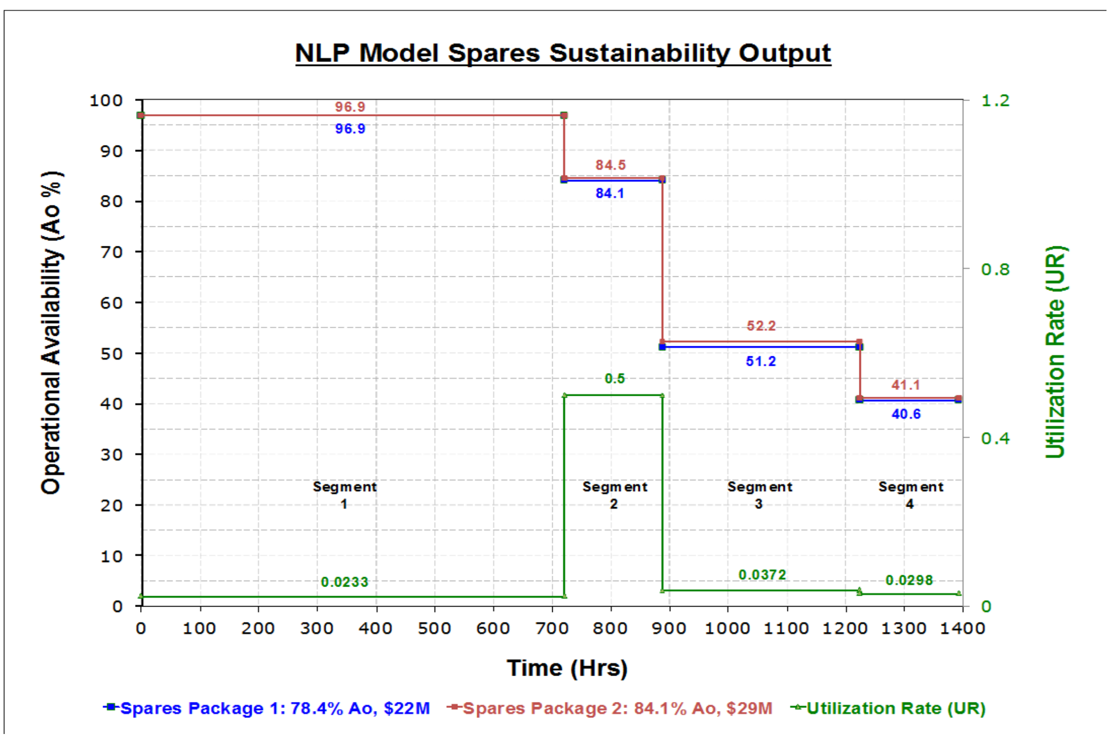


Figure 4-4. Sustainability Analyses of Spares Packages

From Figure 4-4, the Ao achieved in each segment is obtained for both spares packages. It can be observed that the Ao performance decreases over the four segments with the largest decrease observed in Segment 3. The spares optimization in the prior stage ensures that enough spares are catered for operations in the highest intensity segment (i.e. Segment 2) with the longest sustained OD TAT (i.e. Segment 4), that is why Segment 2's Ao achievement would always hover above the desired optimization Ao (78.4% and 84.1% respectively for Packages 1 and 2). The effects of embargo on OD TAT would therefore be felt in downstream segments after Segment 2 and the pipeline increases more significantly for OD TAT items, culminating to large decrease in Ao expected in Segment 3. The pipeline eventually stabilizes since UR is reduced to normal operational levels in Segment 4. Although this results in further Ao reduction into Segment 4 but it occurs at a rate less than Segment 3.

The insignificant practical differences between the packages' segment Ao variations are also noteworthy. Differing only by a maximum of 1% in all segments (e.g. 51.2% vs 52.2% in Segment 3), either package can sufficiently support the assumed operational profile. This means that the concept of diminishing marginal return holds and any additional spending on spares would not translate to higher Ao achievement. To support this notion, package 1 was selected on the premise that "critical" spares (e.g. the Engine LRU that effects a higher impact on total system backorder) were catered to bring about higher marginal benefit and Package 2 adds only to very slight increase in that benefit by increase spending on "non-critical" spares. When a sustainability period is imposed, the critical spares are consumed in both packages and the overall impact on

system backorders is the same. As such, the systemic Ao reduction would be similar in both cases, differing only by the slight effect of additional “non-critical” spares.

Overall, these observations allow analysts to critically examine the effort of spares optimization to evaluate the impact on sustainability performance and better position them in such inventory modeling domain knowledge. Both the optimization and sustainability models must be utilized in synchronized mode to create better sense and decision making in spares acquisition, trading between their costs, benefits and effects.

Model Run-Time Performance

With reference to Table 2-1 of the literature review section, one of OPUS10 limitations was the need for considerable effort in constructing the data and model inputs. The objective in OPUS10 was to eliminate the need to understand the optimization engine but this inevitably meant more time spent on customizing the information to a form suitable for the software. In comparison, the NLP model provides the same WYSIWYG platform for both data inputs and model construction. There is no requirement to further manipulate the data as it is already entered in a form built for the modeling phase. Although Solver run-time is not as comparable to the speed of OPUS10 analytical engine, the overall effort to conduct an analysis is substantially less. Table 4-1 summarizes the time comparison between the two platforms in carrying out optimization studies:

Category	Sequential tasks for a single analysis	OPUS10 Model Analysis Time (mins)	NLP Model Analysis Time (mins)
Data Entry	Collate and manipulate input data in Excel	15	15
	Convert input data to software input format	30	Nil
Modeling	Create / Modify existing software's operations and logistics profile model	25	15
	Input of data into software	10	Nil
Results Output	Generate run results	5	15
	Analyze results	5	5
Total Time Required		**90 mins**	**50 mins**

Table 4-1. Comparison of Time Required for OPUS10 and NLP Model Studies

With all the favourable observations and analyses of the output results, the NLP model can be concluded as satisfactorily verified and validated for turnkey implementation.

V. Conclusion and Recommendation

This chapter closes out the effort of this research. First, the objectives are re-visited to ensure that the requirements have been met by the research outcomes. Second, the significance of the effort is examined for its relevance in potential applications and benefits in the RSAF's context. Third, recommendations for action are proposed so that follow-on implementation of the research model can be realized. Finally, the research assumptions are reassessed to examine areas where future research can be explored.

Conclusion of Research

The objectives put forth at the start of this research were satisfactorily met. The model provided an *easy-to-use* interface to simultaneously allow the handling of data input and modeling interactions that ensure analysts are able to systematically step through the modeling process. This logical flow also enables the model to customize different maintenance support scenarios, making the solution *versatile* in its adaptation. *Accuracy* was achieved by the ability to model variations of component VTMRs to better represent all failure behaviors. These capabilities were realized through a model designed with readily developed templates for dynamic operational profile conversion and NLP optimization logic, allowing *speedy* analyses to be conducted. The outputs provided insights on the most cost-effective spares proposal. Coupled with the appreciation of spares performance over dynamically changing operations, the model delivered the edge needed to *conduct spares optimization and sustainability analyses for O&S planning and contingency operations*, which would otherwise be difficult in a "black-box" software. Finally, the successful *validation* results culminated the basis for *practical deployment* of the tool for implementation within the RSAF.

Significance of Research

This research is in tandem with AELO's push towards seeking new, agile and responsive logistics solutions to support an expanding RSAF's force structure. As more complex and sophisticated weapon systems are acquired, the requirements change to take new forms and the maintenance support concepts have to be synchronized to better sustain these operations. The optimization/sustainability model developed in this research provides a versatile platform to provide this edge in inventory modeling. It was designed around inventory modeling fundamentals and can be easily adapted to study different reparable maintenance scenarios. The analysts need only modify the model structures to best suit the problem on hand, but the computations are similar. This was possible due to the strength of the WYSIWYG design interface. Moreover, because of this design principle, the analysts are equipped with the tool necessary to deepen their competencies in supply chain management expertise within the inventory-modeling domain. They will be able to conduct swift, accurate and credible inventory spares analyses to support O&S and Contingency operations and hence expand expertise on spares planning for future operating concepts, grounding their knowledge to meet the engineering demand in the Third Generation RSAF.

Recommendations for Action

The research model was developed on a representative set of aircraft sub-system components. The next stage would be to implement a turnkey version to include all components. The 6-steps process of model development, explained in Chapter 3, will logically step the analyst through the model deployment, as it would be done in actual implementation of any optimization and sustainability studies. Further validation should

be conducted, both with OPUS10 and with actual field data (actual component VTMRs and spares utilization rates over time) to solidify the implementation of the model. Once that is achieved, the model can be deployed in contingency operations planning to carry out analyses and real-time performances would aid to improve and modify the model in areas like modeling structures and planning parameters. Subsequent rollout of the model on all aircraft platforms will eventually see widespread adoption and unique modifications tailored to support aircraft-specific maintenance scenarios.

Recommendations for Future Research

Some of the assumptions made in Chapter 2 can be relaxed to develop areas where future research can be explored. First, the assumption of an in-country fighter fleet can be expanded to include various operating sites. The model can be tailored to compute the unique pipeline characteristics that individual sites experience and the spares optimization can be conducted for each site. The overall fleet availability is then aggregated from these individual site performances. However, the behavior of the model needs to be studied further if such expansion can be accommodated while sustaining run-time and accuracy of analysis. Second, while this research assumes Ao performance is affected only by the cost of spares, the variability of other maintenance factors (e.g. MTTR manpower constraints and cannibalization effects) and logistics parameters (e.g. OST and lateral base support) can be studied further to generate more systemic measures on the total effect on operational performance. Third, corrective maintenance MTBF is assumed the driving factor behind the demand rates in the model. The study can be expanded to explore the effects of preventive maintenance policies and how that affects the overall optimization. The resulting stock levels may be used to assess the viability of

conducting preventive maintenance in the sustainability period. Finally, the sustainability analysis portion of the model is an analytical solution and provides a fixed Ao performance metric in each individual segment. However, better fidelity of the Ao on a per unit time basis (e.g. day to day) will better track the time-varying performance and not be confined as a segment metric. This is especially crucial and valuable for decision-making in time-sensitive operations. To deliver this capability, Monte Carlo simulation can be utilized in a secondary model to collect unit time status of spares consumption and backorders count as the aircraft system is subjected to varying utilization; and accordingly the sustainability analysis can be made to output Ao variation over time.

Appendix A

Spares Data

Spare ID (S_{jk})	Aircraft System	LRU Description	SRU Description	SSRU Description	Repair Cap (O, I, LD, OD)	QPNHA	Cost per Unit (USD Million)	Current Stock Level	MTBF of LRU (hrs)	Failure Rate of LRU (Demand Rate per hr)	No. of SRU Demand Occurences (FY11/12)	Failure Rate of SRU (Demand Rate per hr)	No. of SSRU Demand Occurences (FY11/12)	Failure Rate of SSRU (Demand Rate per hr)	VTMR (Variance To Mean Ratio) (Assumed)	MTTR of LRU (hrs)	RLT_{jk} (hrs) (Peacetime)	RLT_{jk} (hrs) (Surge Period)	Spares Tpt time (from operating site to store (hrs)	Total TAT (hrs) (Peacetime)	Total TAT (hrs) (Surge Period)	PLT_{jk} LD SSRU (hrs)	Holdg Cost Rate LD SSRU (% of unit cost)	Ordering Cost LD SSRU (fixed order cost $)
	Propulsion System					1																		
S1		Engine			LI	1	6.9720	5	333.33	0.00300003					0.75	2	48	24	0.5	50.5	26.5			
S1-1			Fan		LI	1	0.8780	1			5	0.000714293			0.75		144	72	0.5	144.5	72.5			
S1-1-1				Fan Bearing	LD	1	0.0033	1					1	0.000142859	0.75		2160	168	0.5	2160.5	168.5	4320	0.25	100
S1-1-2				Fan Blade	LD	21	0.0005	25					2	1.36056E-05	0.75		2160	168	0.5	2160.5	168.5	4320	0.25	100
S1-1-3				Stator Assy	LD	1	0.0451	1					1	0.000142859	0.75		2160	168	0.5	2160.5	168.5	4320	0.25	100
S1-1-4				Drum Rotor	LD	1	0.1672	1					1	0.000142859	0.75		2160	168	0.5	2160.5	168.5	4320	0.25	100
S1-2			Core		LI	1	3.8544	1			6	0.000857151			0.75		144	72	0.5	144.5	72.5			
S1-2-1				Chamber Assy	OD	1	0.1798	2					2	0.000285717	0.75		5760	5760	0.5	5760.5	5760.5			
S1-2-2				Mainfold Bearing	OD	1	0.0018	1					3	0.000428576	0.75		5760	5760	0.5	5760.5	5760.5			
S1-2-3				Core Assy	OD	1	0.2322	1					1	0.000142859	0.75		5760	5760	0.5	5760.5	5760.5			
S1-3			HPT/LPT		OD	1	0.3462	2			1	0.000142859			0.75		5760	5760	0.5	5760.5	5760.5			
S1-4			Aug		OD	1	0.8791	1			1	0.000142859			0.75		5760	5760	0.5	5760.5	5760.5			
S1-5			Gearbox		OD	1	0.1867	1			8	0.001142869			0.75		5760	5760	0.5	5760.5	5760.5			
	Fuel System					1																		
S2		Fuel Pump			LI	2	0.0126	3	237	0.004219409					0.75	2	144	72	0.5	146.5	74.5			
S2-1			Fuel Pump Motor		LD	1	0.0082	1			5	0.002637131			0.75		2160	168	0.5	2160.5	168.5			
S2-2			Fuel Pump Lever		LD	1	0.0035	2			3	0.001582278			0.75		2160	168	0.5	2160.5	168.5			
S3		Fuel Cell Assy			LI	1	0.0428	1	425	0.002352941					0.75	2	144	72	0.5	146.5	74.5			
S4		Fuel Flow Proportioner			LI	1	0.0478	2	440	0.002272727					0.75	2	144	72	0.5	146.5	74.5			
S5		Fuel Control Unit			LI	1	0.0166	1	576	0.001736111					0.75	2	144	72	0.5	146.5	74.5			
S6		Fuel Shutoff Valve			LI	4	0.0011	4	623	0.001605136					0.75	2	144	72	0.5	146.5	74.5			
	Hydraulic System					1																		
S7		Hydraulic Pump			LI	2	0.0138	2	1206	0.000829187					0.75	2	144	72	0.5	146.5	74.5			
S8		Hydraulic Motor			LI	1	0.0146	4	223	0.004484305					0.75	2	144	72	0.5	146.5	74.5			
S9		Hydraulic Actuator			LI	1	0.0205	1	798	0.001253133					0.75	2	144	72	0.5	146.5	74.5			
S10		Hydraulic Control Unit			LI	1	0.0163	2	798	0.001253133					0.75	2	144	72	0.5	146.5	74.5			
S11		Hydraulic Pressure Transmitter			LI	2	0.0050	1	142	0.007042254					0.75	2	144	72	0.5	146.5	74.5			
	Flt Ctrl System					1																		
S12		Digital Flight Control Computer			OD	1	0.1680	1	402	0.002487562					3	2	5760	5760	0.5	5762.5	5762.5			
S13		Aft Station Interface Unit			OD	1	0.1666	1	211	0.004739336					3	2	5760	5760	0.5	5762.5	5762.5			
S14		AOA Indexer			OD	2	0.0024	2	308	0.003246753					3	2	5760	5760	0.5	5762.5	5762.5			
S15		Rate Gyro			OD	3	0.0234	2	223	0.004484305					3	2	5760	5760	0.5	5762.5	5762.5			
	Weap. Del. System					1																		
S16		Enhanced Central interface Unit			LI	1	0.2763	2	750	0.001333333					3	2	144	72	0.5	146.5	74.5			
S17		Master Arm Relay Matrix Assy			LI	1	0.0138	2	298	0.003355705					3	2	144	72	0.5	146.5	74.5			
S18		Launcher Adaptor Unit			LI	2	0.0551	1	125	0.008					3	2	144	72	0.5	146.5	74.5			

Appendix B

Combined Spares Data and Logistics Parameters (Propulsion System Excerpt)

Aircraft System	Propulsion System												
Spare ID (S_{ijk})	S1	S1-1	S1-1-1	S1-1-2	S1-1-3	S1-1-4	S1-2	S1-2-1	S1-2-2	S1-2-3	S1-3	S1-4	S1-5
LRU Description	Engine												
SRU Description		Fan					Core				HPT/LPT	Aug	Gearbox
SSRU Description			Fan Bearing	Fan Blade	Stator Assy	Drum Rotor		Chamber Assy	Mainfold Bearing	Core Assy			
Repair Cap (O, I, LD, OD)	LI	LI	LD	LD	LD	LD	LI	OD	OD	OD	OD	OD	OD
QPA (QPNHA)	1	1	1	21	1	1	1	1	1	1	1	1	1
Cost per Unit (USD Million)	6.9720	0.8780	0.0033	0.0005	0.0451	0.1672	3.8544	0.1798	0.0018	0.2322	0.3462	0.8791	0.1867
Current Stock Level	5	1	1	25	1	1	1	2	1	1	2	1	1
MTBF of LRU (hrs)	333.33												
Failure Rate of LRU (Demand Rate per hr)	0.00300003												
No. of SRU Demand Occurences (FY11/12)		5					6				1	1	8
Failure Rate of SRU (Demand Rate per hr)		0.000714293					0.000857151				0.000142859	0.000142859	0.001142869
No. of SSRU Demand Occurences (FY11/12)			1	2	1	1		2	3	1			
Failure Rate of SSRU (Demand Rate per hr)			0.000142859	1.36056E-05	0.000142859	0.000142859		0.000285717	0.000428576	0.000142859			
All LI Failure Rate	0.00300003	0.000714293					0.000857151						
All LD Failure Rate			0.000142859	1.36056E-05	0.000142859	0.000142859							
All OD Failure Rate								0.000285717	0.000428576	0.000142859	0.000142859	0.000142859	0.001142869
VTMR (Variance To Mean Ratio) (Assumed)	0.75	0.75	0.75	0.75	0.75	0.75	0.75	0.75	0.75	0.75	0.75	0.75	0.75
MTTR of LRU (hrs)	2												
RLT_{ijk} (hrs) (Peacetime)	48	144	2160	2160	2160	2160	144	5760	5760	5760	5760	5760	5760
RLT_{ijk} (hrs) (Surge Period)	72	72	168	168	168	168	72	5760	5760	5760	5760	5760	5760
Spares Tpt time (from store to operating site) (hrs)	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5
Total TAT (hrs) (Peacetime)	50.5	144.5	2160.5	2160.5	2160.5	2160.5	144.5	5760.5	5760.5	5760.5	5760.5	5760.5	5760.5
Total TAT (hrs) (Surge Period)	74.5	72.5	168.5	168.5	168.5	168.5	72.5	5760.5	5760.5	5760.5	5760.5	5760.5	5760.5
PLT_{ijk} LD SSRU (hrs)			4320	4320	4320	4320							
Holdg Cost Rate LD SSRU (% of unit cost)			0.25	0.25	0.25	0.25							
Ordering Cost LD SSRU (fixed order cost $)			100	100	100	100							

Appendix C

Dynamic Operational Profile Conversion Model (4-segment Sustainability Period)

Step 1: Ao Boundary Condition Analysis (Determine Max UR Segment)

* Operational Availability Ao = (MTBF / UR) / [(MTBF / UR) + MTTR + MSD] {where MSD = Mean Spares Delay = O&ST + (System EBO/System Demand Rate)} {For Max Ao: Mean Spares Delay = 0, i.e., infinite spares and no order & ship time}

	Segment 1	Segment 2	Segment 3	Segment 4	Segment 5	Segment 6	Segment 7	Segment 8	Segment 9	Segment 10
Segment Duration (Hrs):	720	168	336	168						
Segment Ops Hours:	6720	3360	500	200						
Number of System:	40	40	40	40						
Non-Blank Cells ?:	TRUE	TRUE	TRUE	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
System UR: (Segment Op Hrs / (No. of Systems * Segment Duration))	0.2333	0.5000	0.0372	0.0298						
System MTBF: 1 / Σ (FR of LRU_{ϕ} * QPA_{ϕ})	10.5466	10.5466	10.5466	10.5466	10.5466	10.5466	10.5466	10.5466	10.5466	10.5466
System MTTR:	2	2	2	2						
Order & Ship Time (OST):	0.5	0.5	0.5	0.5						
Max. Ao Achieveable in Individual Segment:	0.9476	0.8940	0.9913	0.9930						
Max. UR:	0.5000	0.5000	0.5000	0.5000	0.5000	0.5000	0.5000	0.5000	0.5000	0.5000

Step 2: Spare Package Determination (Determine Max Pipeline Segment and Compute Weighted TAT)

* Does segment with min. Ao (among the individual segment max Ao) has max pipeline size ?
* Pipeline size = QPA x Failure rate of item x Utilisation rate x Turn Around Time (QPA x FR x UR x TAT) [where item denotes any LRU, SRU or SSRU and TAT is either peacetime or surge depending on segment]
* Weighted Factor (WF) is used when segment with max. pipeline size ≠ segment of max. UR
* $WF = UR_{max.pipeline} / UR_{max}$
* Weighted Local Cap TAT = WF x (Item TAT@max. pipeline) [Applicable for items with LI and LD Cap]
* Average UR = Σ (UR x segment duration) / Σ (segment duration)
* Weighted Overseas TAT = (Average UR / Max. UR) x Total Period Duration [Applicable for items with OD Cap] [Total Period Duration = Σ (segment duration)]

	Segment 1	Segment 2	Segment 3	Segment 4	Segment 5	Segment 6	Segment 7	Segment 8	Segment 9	Segment 10
Total Pipeline Size:	3.1545	2.9062	0.2162	0.1730						
System UR:	0.2333	0.5000	0.0372	0.0298						
All LI: Σ ($QPA_* \times FR_*$)	0.0692	0.0692	0.0692	0.0692	0.0692	0.0692	0.0692	0.0692	0.0692	0.0692
All LI TAT:	144	72	72	72						
All LD: Σ ($QPA_* \times FR_*$)	0.0049	0.0049	0.0049	0.0049	0.0049	0.0049	0.0049	0.0049	0.0049	0.0049
All LD TAT:	2160	168	168	168						
All OD: Σ ($QPA_* \times FR_*$)	0.0295	0.0295	0.0295	0.0295	0.0295	0.0295	0.0295	0.0295	0.0295	0.0295
All OD TAT:	5760	5760	5760	5760						
WF:	1.0000	0.4667	0.4667	0.4667	0.4667	0.4667	0.4667	0.4667	0.4667	0.4667
Average UR:	0.2333	0.2838	0.2161	0.1936	0.1936	0.1936	0.1936	0.1936	0.1936	0.1936
Weighted LI TAT (Computation):	144.0	67.2	67.2	67.2	67.2	67.2	67.2	67.2	67.2	67.2
Weighted LD TAT (Computation):	2160.0	1008.0	1008.0	1008.0	1008.0	1008.0	1008.0	1008.0	1008.0	1008.0
Weighted OD TAT (Computation):	336.0	504.0	529.0	539.0	539.0	539.0	539.0	539.0	539.0	539.0
Weighted LI TAT (For Optimization Model Input)	67.2									
Weighted LD TAT (For Optimization Model Input)	1008.0									
Weighted OD TAT (For Optimization Model Input)	539.0									
Max UR (For Optimization Model Input)	0.5000									

Step 3: Segment Ao Determination (Determine Parameters for Sustainability Analyses)

	Segment 1	Segment 2	Segment 3	Segment 4	Segment 5	Segment 6	Segment 7	Segment 8	Segment 9	Segment 10
Original Segment UR (For Sustainability Analysis Input)	0.2333	0.5000	0.0372	0.0298						
Original Segment LI TAT (For Sustainability Analysis Input)	144.0	72.0	72.0	72.0						
Original Segment LD TAT (For Sustainability Analysis Input)	2160.0	168.0	168.0	168.0						
Weighted Segment OD TAT (For Sustainability Analysis Input)	720.0	504.0	7109.8	9055.2						

Appendix D

Item Backorders and System Performance Computations (Propulsion System)

Aircraft System	Propulsion System												
Spare ID (S_{ijk})	S1	S1-1	S1-1-1	S1-1-2	S1-1-3	S1-1-4	S1-2	S1-2-1	S1-2-2	S1-2-3	S1-3	S1-4	S1-5
LRU Description	Engine												
SRU Description		Fan					Core				HPT/LPT	Aug	Gearbox
SSRU Description			Fan Bearing	Fan Blade	Stator Assy	Drum Rotor		Chamber Assy	Mainfold Bearing	Core Assy			
Repair Cap (O, I, LD, OD)	LI	LI	LD	LD	LD	LD	LI	OD	OD	OD	OD	OD	OD
QPA (QPNHA)	1	1	1	21	1	1	1	1	1	1	1	1	1
Cost per Unit (USD Million)	6.972	0.87796518	0.00332	0.000519	0.045126	0.167194	3.85439465	0.179815	0.00183758	0.2322	0.34621461	0.87905211	0.18674132
Current Stock Level	5	1	1	25	1	1	1	2	1	1	2	1	1
MTBF of LRU (hrs)	333.33												
Failure Rate of LRU (Demand Rate per hr)	0.00300003												
No. of SRU Demand Occurences (FY11/12)		5					6				1	1	8
Failure Rate of SRU (Demand Rate per hr)		0.000714293					0.000857151				0.000142859	0.000142859	0.001142869
No. of SSRU Demand Occurences (FY11/12)			1	2	1	1		2	3	1			
Failure Rate of SSRU (Demand Rate per hr)			0.000142859	1.36056E-05	0.000142859	0.000142859		0.000285717	0.000428576	0.000142859			
All LI Failure Rate	0.00300003	0.000714293					0.000857151						
All LD Failure Rate			0.000142859	1.36056E-05	0.000142859	0.000142859							
All OD Failure Rate								0.000285717	0.000428576	0.000142859	0.000142859	0.000142859	0.001142869
VTMR (Variance To Mean Ratio) (Assumed)	0.75	0.75	0.75	0.75	0.75	0.75	0.75	0.75	0.75	0.75	0.75	0.75	0.75
MTTR of LRU (hrs)	2												
RLT_{ijk} (hrs) (Peacetime)	48	144	2160	2160	2160	2160	144	5760	5760	5760	5760	5760	5760
RLT_{ijk} (hrs) (Surge Period)	72	72	168	168	168	168	72	5760	5760	5760	5760	5760	5760
Spares Tpt time (from store to operating site) (hrs)	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5
Total TAT (hrs) (Peacetime)	50.5	144.5	2160.5	2160.5	2160.5	2160.5	144.5	5760.5	5760.5	5760.5	5760.5	5760.5	5760.5
Total TAT (hrs) (Surge Period)	74.5	72.5	168.5	168.5	168.5	168.5	72.5	5760.5	5760.5	5760.5	5760.5	5760.5	5760.5
PLT_{ijk} LD SSRU (hrs)			4320	4320	4320	4320							
Holdg Cost Rate LD SSRU (% of unit cost)			0.25	0.25	0.25	0.25							
Ordering Cost LD SSRU (fixed order cost $)			100	100	100	100							
Backorder Computation													
LRU, SRU or SSRU ?	LRU	SRU	SSRU	SSRU	SSRU	SSRU	SRU	SSRU	SSRU	SSRU	SRU	SRU	SRU
Weighted TAT (LI, LD or OD)	67.2	67.2	1008	1008	1008	1008	67.2	539	539	539	539	539	539
Expected Backorder of SSRU (EBO S_{ijk})			0.1440	0.0137	0.1440	0.1440		0.1540	0.2310	0.0770			
Variance Backorder of SSRU (VBO S_{ijk})			0.1233	0.0135	0.1233	0.1233		0.1303	0.1776	0.0711			
Standard Deviation Backorder of SSRU (SDBO S_{ijk})			0.3511	0.1163	0.3511	0.3511		0.3610	0.4215	0.2666			
Expected Pipeline Size of SRU E[X_{ij}]		0.4937					0.5196				0.1540	0.1540	1.2320
Variance Pipeline Size of SRU V[X_{ij}]		0.4313					0.4366				0.1481	0.1481	1.1055
Expected Backorder of SRU (EBO S_{ij})		0.4937					0.5196				0.1540	0.1540	1.2320
Variance Backorder of SRU (VBO S_{ij})		0.4328					0.4521				0.1481	0.1481	1.1055
Standard Deviation Backorder of SRU (SDBO S_{ij})		0.6579					0.6724				0.3848	0.3848	1.0514
Expected Pipeline Size of LRU E[X_i]	2.7549												
Variance Pipeline Size of LRU V[X_i]	2.4882												
Expected Backorder of LRU (EBO S_i)	0.0000												
Variance Backorder of LRU (VBO S_i)	0.0000												
Standard Deviation Backorder of LRU (SDBO S_i)	0.0000												

Aircraft System	Propulsion System												
Spare ID (S_{jk})	S1	S1-1	S1-1-1	S1-1-2	S1-1-3	S1-1-4	S1-2	S1-2-1	S1-2-2	S1-2-3	S1-3	S1-4	S1-5
LRU Description	Engine												
SRU Description		Fan					Core				HPT/LPT	Aug	Gearbox
SSRU Description			Fan Bearing	Fan Blade	Stator Assy	Drum Rotor		Chamber Assy	Mainfold Bearing	Core Assy			
Repair Cap (O, I, LD, OD)	LI	LI	LD	LD	LD	LD	LI	OD	OD	OD	OD	OD	OD
QPA (QPNHA)	1	1	1	21	1	1	1	1	1	1	1	1	1
Cost per Unit (USD Million)	6.972	0.87796518	0.00332	0.000519	0.045126	0.167194	3.85439465	0.179815	0.00183758	0.2322	0.34621461	0.87905211	0.18674132
Current Stock Level	5	1	1	25	1	1	1	2	1	1	2	1	1
MTBF of LRU (hrs)	333.33												
Failure Rate of LRU (Demand Rate per hr)	0.00300003												
No. of SRU Demand Occurences (FY11/12)		5					6				1	1	8
Failure Rate of SRU (Demand Rate per hr)		0.000714293					0.000857151				0.000142859	0.000142859	0.001142869
No. of SSRU Demand Occurences (FY11/12)			1	2	1	1		2	3	1			
Failure Rate of SSRU (Demand Rate per hr)			0.000142859	1.36056E-05	0.000142859	0.000142859		0.000285717	0.000428576	0.000142859			
All LI Failure Rate	0.00300003	0.000714293					0.000857151						
All LD Failure Rate			0.000142859	1.36056E-05	0.000142859	0.000142859							
All OD Failure Rate								0.000285717	0.000428576	0.000142859	0.000142859	0.000142859	0.001142869
VTMR (Variance To Mean Ratio) (Assumed)	0.75	0.75	0.75	0.75	0.75	0.75	0.75	0.75	0.75	0.75	0.75	0.75	0.75
MTTR of LRU (hrs)	2												
RLT_{jk} (hrs) (Peacetime)	48	144	2160	2160	2160	2160	144	5760	5760	5760	5760	5760	5760
RLT_{jk} (hrs) (Surge Period)	72	72	168	168	168	168	72	5760	5760	5760	5760	5760	5760
Spares Tpt time (from store to operating site) (hrs)	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5
Total TAT (hrs) (Peacetime)	50.5	144.5	2160.5	2160.5	2160.5	2160.5	144.5	5760.5	5760.5	5760.5	5760.5	5760.5	5760.5
Total TAT (hrs) (Surge Period)	74.5	72.5	168.5	168.5	168.5	168.5	72.5	5760.5	5760.5	5760.5	5760.5	5760.5	5760.5
PLT_{jk} LD SSRU (hrs)			4320	4320	4320	4320							
Holdg Cost Rate LD SSRU (% of unit cost)			0.25	0.25	0.25	0.25							
Ordering Cost LD SSRU (fixed order cost $)			100	100	100	100							
Spares Optimization/Sustainability & System Performance Measures													
Optimized No. of Spares (NLP Model Output)													
Spares Constraint	12	12	1	1	1	1	7	1	1	1	1	1	2
Optimized No. of Spares (with adjusted EOQ qty for LD SSRUs)	0	0	6	5	2	2	0	0	0	0	0	0	0
LD SSRU Re-order Point			0	0	0	0							
Cost of Spares ($) (NLP Model Output) (C*S)	0	0	0	0	0	0	0	0	0	0	0	0	0
Cost of Spares ($) (with adjusted EOQ qty for LD SSRUs) (C*S)	0	0	0	0	0	0	0	0	0	0	0	0	0
Total Cost of Spares ($) (NLP Model Output) (Σ C*S)	**0**												
Spares Budget ($)	**29**												
Total Cost of Spares ($) (with adjusted EOQ qty for LD SSRUs) (Σ C*S)	**0.384419114**												
System Expected Backorders (LRUs only)	**32.4431**												
System MTBF (hrs) (LRUs only)	**10.5466**												
System MTTR (hrs) (LRUs only)	**2.0000**												
OST (hrs) (Site to Store)	**0.5000**												
Utilization Rate (UR)	**0.5000**												
System Expected Availability (Ao) (%)	**5.77%**												

Appendix E

Excel VBA® Macro Programming Scripts

EBO and VBO for Poisson Distribution:

```
Public Function EBOPOISSON(Mean As Double, Stock As Integer) As Double
   EBOPOISSON = Mean - Stock
   For x = 0 To Stock
      EBOPOISSON = EBOPOISSON + (Stock - x) *
Application.WorksheetFunction.Poisson(x, Mean, False)
   Next x
End Function
```

```
Public Function VBOPOISSON(Mean As Double, Stock As Integer) As Double
   VBOPOISSON = 0
   For x = (Stock + 1) To 999
      VBOPOISSON = VBOPOISSON + ((x - Stock) ^ 2) *
Application.WorksheetFunction.Poisson(x, Mean, False)
   Next x
   VBOPOISSON = VBOPOISSON - (EBOPOISSON(Mean, Stock) ^ 2)

End Function
```

EBO and VBO for Binomial Distribution:

```
Public Function EBOBINOM(Mean As Double, Stock As Integer, VTMR As Double) As
Double
   n = Application.WorksheetFunction.RoundDown(((Mean / (1 - VTMR)) + 0.99), 0)
   p = Mean / n
   EBOBINOM = Mean - Stock
   For x = 0 To Stock
      EBOBINOM = EBOBINOM + (Stock - x) *
Application.WorksheetFunction.BinomDist(x, n, p, False)
   Next x
End Function
```

```
Public Function VBOBINOM(Mean As Double, Stock As Integer, VTMR As Double)
As Double
   n = Application.WorksheetFunction.RoundDown(((Mean / (1 - VTMR)) + 0.99), 0)
   p = Mean / n
   VBOBINOM = 0
   For x = (Stock + 1) To n
      VBOBINOM = VBOBINOM + ((x - Stock) ^ 2) *
Application.WorksheetFunction.BinomDist(x, n, p, False)
   Next x
   VBOBINOM = VBOBINOM - (EBOBINOM(Mean, Stock, VTMR) ^ 2)

End Function
```

EBO and VBO for Negative Binomial Distribution:

```
Public Function COMBINATIO(a, x) As Double
   If (x = 0) Then
      COMBINATIO = 1
   ElseIf (x = 1) Then
      COMBINATIO = a
   ElseIf (x = 2) Then
      COMBINATIO = ((a + x - 1) * a) / Application.WorksheetFunction.Fact(x)
   ElseIf (x = 3) Then
      COMBINATIO = ((a + x - 1) * (a + x - 2) * a) /
Application.WorksheetFunction.Fact(x)
   ElseIf (x = 4) Then
      COMBINATIO = ((a + x - 1) * (a + x - 2) * (a + x - 3) * a) /
Application.WorksheetFunction.Fact(x)
   ElseIf (x = 5) Then
      COMBINATIO = ((a + x - 1) * (a + x - 2) * (a + x - 3) * (a + x - 4) * a) /
Application.WorksheetFunction.Fact(x)
   ElseIf (x = 6) Then
      COMBINATIO = ((a + x - 1) * (a + x - 2) * (a + x - 3) * (a + x - 4) * (a + x - 5) * a)
/ Application.WorksheetFunction.Fact(x)
   ElseIf (x = 7) Then

“Recursive”, continue to cover till x = 50

   Else
   End….
   End If
End Function
```

```
Public Function EBONEGBINOM(Mean As Double, Stock As Integer, VTMR As
Double) As Double
   a = Mean / (VTMR - 1)
   b = (VTMR - 1) / VTMR
   EBONEGBINOM = Mean - Stock
   For x = 0 To Stock
      EBONEGBINOM = EBONEGBINOM + (Stock - x) * ((COMBINATIO(a, x)) * (b
^ x) * ((1 - b) ^ a))
   Next x
End Function
```

```
Public Function VBONEGBINOM(Mean As Double, Stock As Integer, VTMR As
Double) As Double
   a = Mean / (VTMR - 1)
   b = (VTMR - 1) / VTMR
   VBONEGBINOM = 0
   For x = (Stock + 1) To 50
      VBONEGBINOM = VBONEGBINOM + ((x - Stock) ^ 2) * ((COMBINATIO(a,
x)) * (b ^ x) * ((1 - b) ^ a))
   Next x
   VBONEGBINOM = VBONEGBINOM - (EBONEGBINOM(Mean, Stock, VTMR) ^
2)

End Function
```

Appendix F

Non-Linear Programming Logic

Logic:

$$\mathit{Max.}$$

$$\frac{100 * [\, MTBF_{system} / UR \,]}{\left[MTBF_{system} / UR \right] + \left[MTTR_{system} + \left(MTBF_{system} * \sum_{i=1}^{i} EBO_i \right) \right]}$$

$$\mathit{s.t.}$$

$$\sum_{i=1}^{i} C_i S_i \leq Budget(\$)$$

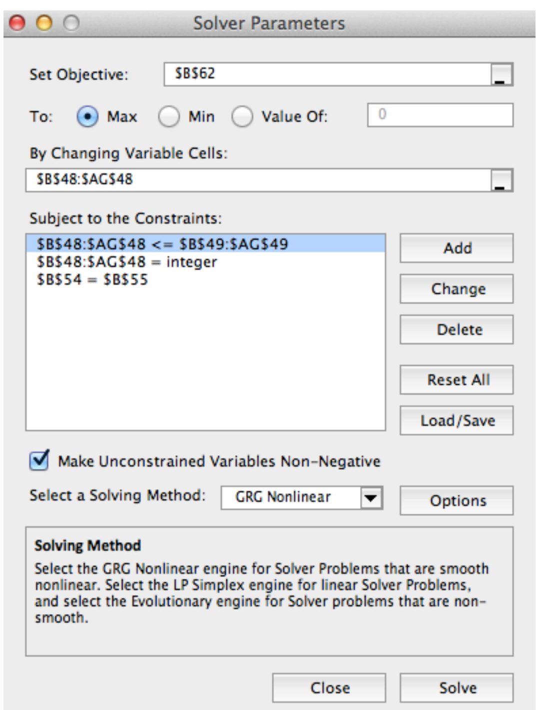
where

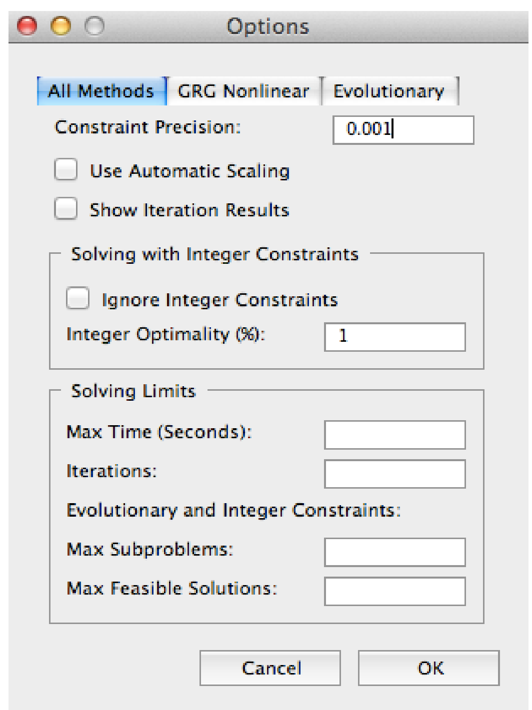
$EBO_i = Expected\ Backorder\ of\ LRU_i$

$C_i = Unit\ Cost\ of\ LRU_i$

$S_i = Spare\ Qty\ of\ LRU_i \in Z^{+}\ (non-negative\ integer)$

Microsoft Excel Solver® Setup:





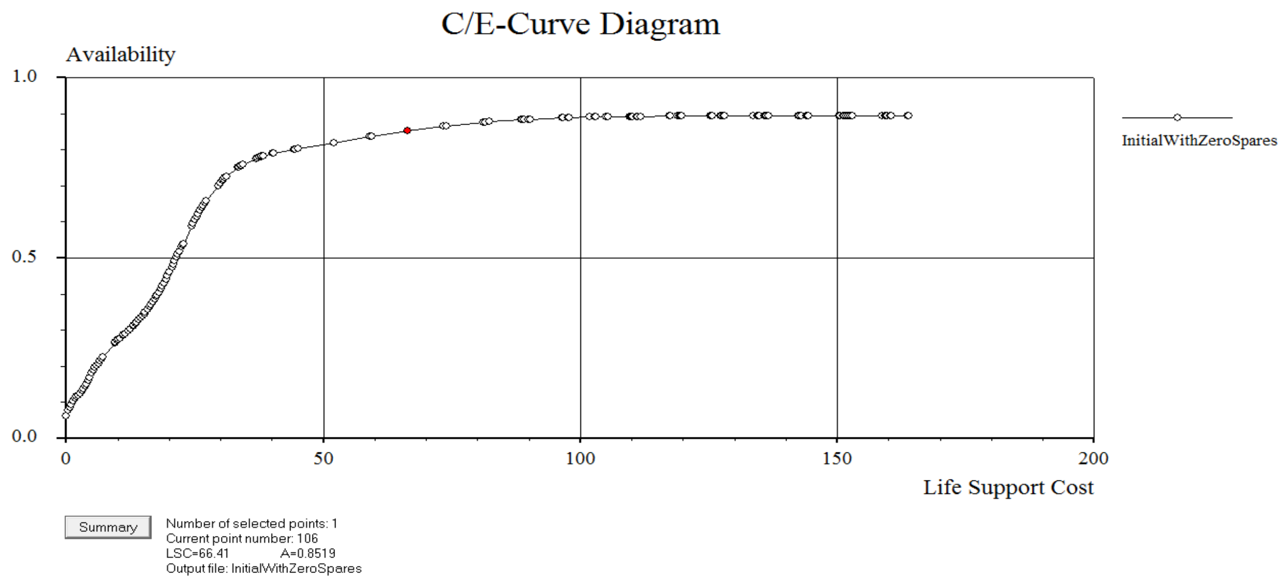
Appendix G

NLP Poisson Model vs OPUS Model Data Output

VTMR = 1 for all items

Appendix H

OPUS Model Cost-Effectiveness Output



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Vita

Military Expert 5 (ME5 - Major equivalent) Edmund K.W. Pek is a Material Acquisition Engineering Officer with the Republic of Singapore Air Force (RSAF). He was enlisted as an F-5 Aircraft J85 Engine Senior Technician in August 1997. Following officer conversion, he was commissioned in April 2000. ME5 Pek's assignments in maintenance squadrons include Officer-In-Charge (OIC) A-4 Skyhawk Maintenance Section, Aircraft Maintenance Flight, Air Logistics Squadron, Tengah Air Base (2000 – 2004); and Deputy Officer Commanding (Dy OC) Maintenance Control Flight, Air Logistics Squadron, Tengah Air Base (2004). Following his maintenance assignments, he was awarded the Singapore Armed Forces (SAF) Academic Training Award (ATA) to pursue a Mechanical Aerospace Engineering Degree in Nanyang Technological University (NTU) of Singapore. Graduated with an Honours Bachelor degree, he was assigned to Headquarters RSAF (HQ RSAF) in July 2007 as aircraft material acquisition staff officer in Materials System Branch (MSB) of Air Engineering and Logistics Department (ALD). Progressed to head the fighters/ transports/ air defence weapon systems acquisition section in July 2010, he led the material acquisition program for the F-35 Joint Strike Fighter platform. Subsequently, he was conferred the prestigious SAF Postgraduate Award (SPA) in Jan 2012 to pursue double masters degrees in Defence Technology and Systems (MDTS) in National University of Singapore (NUS) and Logistics Supply Chain Management (LSCM) in the Air Force Institute of Technology (AFIT), Wright-Patterson Air Force Base (WPAFB), United States Air Force. Following graduation, he will be assigned to the Unmanned Aerial Vehicle Command (UC) as Mechanical OC.

REPORT DOCUMENTATION PAGE	*Form Approved* *OMB No. 074-0188*

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1. REPORT DATE *(DD-MM-YYYY)*	**2. REPORT TYPE**	**3. DATES COVERED** *(From – To)*
15/09/2013	Master's Thesis	01/10/2012 – 15/09/2013

4. TITLE AND SUBTITLE Development of Availability and Sustainability Spares Optimization Models for Aircraft Reparables	**5a. CONTRACT NUMBER**
	5b. GRANT NUMBER
	5c. PROGRAM ELEMENT NUMBER
6. AUTHOR(S) Pek, Edmund K.W., Major (Military Expert 5)	**5d. PROJECT NUMBER**
	5e. TASK NUMBER
	5f. WORK UNIT NUMBER
7. PERFORMING ORGANIZATION NAMES(S) AND ADDRESS(S) Air Force Institute of Technology Graduate School of Engineering and Management (AFIT/EN) 2950 Hobson Street, Building 642 WPAFB OH 45433-7765	**8. PERFORMING ORGANIZATION REPORT NUMBER** AFIT-ENS-13-S-4
9. SPONSORING/MONITORING AGENCY NAME(S) AND ADDRESS(ES) Col. Lim Soon Chia Deputy Chief Research & Technology Officer (Ops)/(C4) Defence Research and Technology Office (DRTO) 303, Gombak Drive, Ministry of Defence, Singapore 669645 DID: +65-67683181; Email: lim_soon_chia@mindef.gov.sg	**10. SPONSOR/MONITOR'S ACRONYM(S)** MINDEF
	11. SPONSOR/MONITOR'S REPORT NUMBER(S)

12. DISTRIBUTION/AVAILABILITY STATEMENT

Distribution A. Approved for Public Release; Distribution Unlimited.

13. SUPPLEMENTARY NOTES

14. ABSTRACT

The Republic of Singapore Air Force (RSAF) conducts Logistics Support Analysis (LSA) studies in various engineering and logistics efforts on the myriad of weapon systems. In these studies, inventory spares provisioning, availability and sustainability analyses are key focus areas to ensure asset sustenance. In particular, OPUS10, a commercial-off-the-shelf software, is extensively used to conduct reparable spares optimization in acquisition programs. However, it is limited in its ability to conduct availability and sustainability analyses of time-varying operational demands, crucial in Operations & Support (O&S) and contingency planning. As the RSAF seeks force structure expansion to include more sophisticated weapon systems, the operating environment will become more complex. Agile and responsive logistics solutions are needed to ensure the RSAF engineering community consistently pushes for deepening competencies, particularly in LSA capabilities. This research is aimed at the development of a model solution that combines optimization and sustainability capabilities to meet the dynamic requirements in O&S and contingency planning. In particular, a unique dynamic operational profile conversion model was developed to realize these capabilities. It is envisaged that the research would afford the ease of use, versatility, speed and accuracy required in LSA studies, to provide the necessary edge in inventory reparable spares modeling.

15. SUBJECT TERMS

Inventory Modeling, Optimization, Availability, Sustainability, Backorders, Spares

16. SECURITY CLASSIFICATION OF:			**17. LIMITATION OF ABSTRACT**	**18. NUMBER OF PAGES**	**19a. NAME OF RESPONSIBLE PERSON** Dr. Alan W. Johnson, AFIT/ENS
a. REPORT	**b. ABSTRACT**	**c. THIS PAGE**			**19b. TELEPHONE NUMBER** *(Include area code)*
U	U	UU	UU	86	(937) 255-3636, ext 4703 (Alan.Johnson@afit.edu)

Standard Form 298 (Rev. 8-98)
Prescribed by ANSI Std. Z39-18